

Exhibit 1

**UNITED STATES DISTRICT COURT
DISTRICT OF NEW JERSEY**

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IN RE: AETNA UCR LITIGATION) **MDL NO. 2020**
) (**No. 2:07-CV-3541**)
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EXPERT REPORT OF DR. ROBIN CANTOR

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I. Qualifications

1. My name is Robin Cantor. I am a Principal in the Alexandria, VA office of Exponent, Inc. I specialize in applied economics, environmental and energy economics, statistics, and risk management. I have a B.S. in mathematics from Indiana University of Pennsylvania with a specialization in statistics and a Ph.D. in economics from Duke University with a specialization in econometrics.
2. Prior to joining Exponent, I was a Managing Director in the Insurance and Claims Services practice of Navigant Consulting, Inc. I led the Liability Estimation and Insurance Coverage practice.
3. I was a Principal and Managing Director of the Environmental and Insurance Claims Practice of LECG, LLC.
4. My responsibilities include conducting complex economic, statistical, and risk analyses for consulting, litigation support, and expert testimony, as well as managing a staff of internal and external professionals.
5. I was the Program Director for Decision, Risk, and Management Sciences, a research program of the National Science Foundation (“NSF”) and a senior researcher at Oak Ridge National Laboratory. I am a past Coordinator and grants manager for the NSF Human Dimensions of Global Change, the NSF Methods and Models for Integrated Assessment, and the NSF/EPA Decision Making and Valuation for Environmental Policy.
6. I have a faculty appointment in the Graduate Part-time Program in Environmental Engineering, Science and Management of the Johns Hopkins University.
7. I have more than 25 years of research, teaching, and consulting expertise. My testimonial experience includes analysis of economic damages in commercial litigation, economic analysis of class certification issues, product liability estimation in bankruptcy matters, product liability analysis for insurance disputes, statistical analysis of asbestos settlements, analysis of premises and product claims, cost contribution allocation in Superfund disputes, analysis of derailment risks, and reliability of statistical models and estimation methods.
8. I was the 2002 President of the Society for Risk Analysis. In 2001, I was appointed as a member of the Research Strategies Advisory Committee of the U.S. Environmental Protection Agency's Science Advisory Board. I am a past President of the Board of Directors for MATRIX, The Business Center for Women and Minorities. I am a member of the Society for Risk Analysis, the American Economic Association, and the Women's Council on Energy and the Environment. I serve or have served on science review and advisory panels for the National Academies of Science, the National Science Foundation, the Johns Hopkins University Graduate Part-Time Program in Environmental Engineering and Science, the National Center for Environmental Decision-making Research, the Carnegie Council on Ethics and International Affairs, the National Oceanic and Atmospheric Administration, the National Academy of Public Administration, and the Consortium for International Earth Science Information Network. I have served on the editorial boards of the Journal of Risk Analysis and the Journal of Risk Research.

9. I have published scholarly articles on numerous areas of economic analysis. I have submitted analysis, testimony and affidavits in federal arbitration, regulatory and Congressional proceedings, and federal and state courts. My publications include refereed journal articles, book chapters, expert reports, reports for federal sponsors, and a co-authored book on economic exchange under alternative institutional and resource conditions.
10. I have been qualified in state and federal court as an expert on economics, including microeconomics, econometrics, cost benefit analysis, cost benefit methodologies, risk management and asbestos claims analysis. I was the expert engaged by the proposed class of corrugated sheet purchasers in *In re Linerboard Antitrust Litigation*, and my analysis was cited favorably by the U.S. Court of Appeals for the Third Circuit.
11. My curriculum vita is attached as Attachment 1 to this report. My testimonial experience in the last four years is attached as Attachment 2. My current billing rate for this engagement is \$570/hour for analysis and testimony. Other Exponent staff members have also worked at my direction on this matter and they have been billed at rates ranging from \$85 to \$335.

II. Assignment

12. I have been engaged by Gibson, Dunn & Crutcher LLP (“Counsel”) on behalf of its clients, Aetna Health Inc. PA, Corp., Aetna Health Management, LLC, Aetna Life Insurance Company, Aetna Health And Life Insurance Company, Aetna Health Inc., Aetna Insurance Company of Connecticut, and Aetna, Inc. (collectively, “Aetna” or “Defendants”¹), to provide an expert opinion in the matters that have been consolidated as *In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation* (MDL No. 2020).
13. I understand that this matter involves three sets of proposed class plaintiffs: (a) health plan members (i.e., individuals enrolled in health plans who received out-of-network (“ONET”) services); (b) medical providers (i.e., individuals who provided healthcare services to members); and (c) associations (i.e., groups that represent providers) (collectively, “Plaintiffs”).² I understand also that plaintiff Weintraub further brings this action against UnitedHealth Group, Inc. (“UHG”) and Ingenix, Inc. (“Ingenix”).
14. In these matters, Plaintiffs allege that (a) due to an inherent conflict of interest, the Ingenix Prevailing Healthcare Charges System (“PHCS”) Database (the “Ingenix Database”) of provider charge information was flawed in its construction and compilation, leading to systematically lower distributions of charges as reported in the Ingenix Database; and (b) when Aetna used these allegedly flawed data to determine the usual, customary and reasonable rates (“UCR”)³ for determining reimbursement of ONET services, Aetna’s reimbursement rates for ONET services were lower than they

¹ In this report, “Defendants” refers only to the referenced Aetna entities and no other parties.

² See Joint Consolidated Amended Class Action Complaint and Demand for Jury Trial, *In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation* (MDL No. 2020 filed Jul. 1, 2009) (the “Complaint”) at ¶ 1.

³ Aetna defines the reasonable and customary amount as “the prevailing charge for the service or supply in the geographic area where it is furnished.” See AET-C00103216. As described in more detail in paragraph 25, the terms of Aetna’s plans vary, and reimbursement for ONET claims may be based on UCR, reasonable, usual and customary, or prevailing charge plan language.

would have been if Aetna had used a data source that did not suffer from the alleged flaws in the Ingenix Database. According to the Complaint, Aetna and other alleged co-conspirators “knowingly created, manipulated and used flawed data to set artificially low reimbursement rates for ONET.”⁴ The Plaintiffs are asserting these claims on behalf of purported classes of members and providers throughout the United States who received or provided any type of medical services on an ONET basis where Aetna allowed less than the provider’s billed charge in determining benefits.⁵

15. The scope of my assignment was (a) to use standard statistical and economic methods to investigate whether there is evidence that the alleged fundamental flaws in the data sampling and compilation methods resulted in a systematic downward skewing of the Ingenix Database values; (b) to investigate whether there is evidence that use of the Ingenix Database values would systematically lead to under reimbursement on an across-the-board basis for all (or nearly all) members of the purported classes; and (c) to consider whether my findings demonstrate statistical or economic conditions that would result in fundamental conflicts among members of the proposed classes, fatal flaws in the methodology to prove class-wide impact, or both.
16. My opinions are based on my understanding of the information available to me as of the date of this report and my experience and training as an economist. In the event that additional relevant materials are made available to me, I will consider such information as necessary. I reserve the right to supplement this report based upon any additional work that I may conduct or supervise from my review of such materials.
17. In conducting my analysis, I collected and reviewed various publicly available information, case pleadings, and certain documents, depositions, interrogatories, and data produced in discovery for this matter. The materials I considered for my analyses are listed in the footnotes of this report and in Attachment 3.

III. Summary of Findings and Opinions

18. In this matter, Plaintiffs allege that Aetna’s behavior related to data contribution and use of the Ingenix Database has been infected by conflicts of interest and conspiratorial conduct. Plaintiffs claim that such behavior has resulted in lowering the upper percentile values of the Ingenix Database that Aetna uses to calculate UCR rates for ONET services. As a result, Plaintiffs allege that members of the proposed classes have been under reimbursed. For the purposes of this report, I have not made any attempt to determine whether Plaintiffs’ allegations regarding Aetna’s or the other alleged co-conspirators’ conduct are true. Rather, my analysis examines whether the alleged common impact follows from the alleged conduct, and whether damages are subject to class-wide proof.
19. Plaintiffs maintain the hypothesis that flawed methodology for data contribution and processing violates the “core concepts” of defining similarly situated charge data, which leads to a downward bias of the values used to determine UCR rates. Under this theory, Plaintiffs maintain that separating dissimilar charge data should result in an increase in

⁴ See, e.g., Complaint at ¶ 5.

⁵ See, e.g., Complaint at ¶¶ 549 and 562.

the UCR rates for members of the proposed classes. A standard statistical illustration of Plaintiffs' theory, however, demonstrates that separating dissimilar charge populations within pricing distributions is likely to *lower* UCR rates for a substantial portion of members of the proposed classes.

20. I also investigated whether a pervasive downward bias in the Ingenix Database values could be demonstrated empirically and whether Plaintiffs' claim that UCR rates were depressed as a result of an alleged downward bias in the Ingenix Database is subject to class-wide proof. My analysis identified a number of sources of industry data that are readily available to Plaintiffs and apparently are free of the alleged unlawful conduct. I find that these data sources are appropriate benchmarks to investigate whether there is class-wide proof that the upper percentile values in the Ingenix Database are downwardly biased.
21. My analysis yields three important results for the consideration of class-wide proof of the alleged under reimbursement of members of the proposed classes:
 - Based on comparisons with the benchmarks, Ingenix Database values are frequently greater than the benchmark values;
 - Based on standard matched-pair analysis, the evidence does not support that on average the Ingenix Database values relevant to the calculation of UCR rates are materially different from the benchmarks; and
 - Comparisons with the benchmark databases fail to support an allegation that Ingenix Database values are lower than the benchmarks across the board. This is the case whether the data are examined nationally, by American Medical Association ("AMA") classes (i.e., sections) of procedures, or by individual medical procedures.
22. My approach follows the same methodology for investigating under reimbursement as the one described by the New York Attorney General in a recent study of the Ingenix Database values.⁶ My analysis indicates, however, fundamentally different results from the conclusions stated in the NYAG Report. When Ingenix Database values are compared to the available benchmarks in the subject counties for the subject services addressed by the NYAG Report, I find evidence of lower values for only one of the five subject counties. Across New York State, my results indicate that Ingenix Database values tend to exceed the benchmark values for the subject services.
23. In combination, the results of the various studies I have conducted are consistent with the conclusion that Plaintiffs cannot show common impact by reference to existing commercial and government benchmarks not infected by the alleged conflict of interest or conspiracy allegations.

⁶ See State of New York, Office of the Attorney General, "Health Care Report: The Consumer Reimbursement System is Code Blue," (Jan. 4, 2009) (the "NYAG Report").

IV. Bases for Opinions

A. Case Background

1. Claims Regarding the Ingenix Database

24. According to the Complaint, Aetna offers health insurance plans that differentiate between coverage to insured individuals (“Members”) for medical treatment obtained from in-network versus ONET providers.⁷ The claims in this case focus on Aetna’s reimbursement for services provided by ONET providers.⁸ According to the Complaint, Aetna promises members to pay for ONET services at a percentage of the lesser of either (a) the actual amount of their medical bills; or (b) the UCR rate for the services provided,⁹ defined as the rate “charged by providers providing such services in the same or similar geographic area for substantially the same service.”¹⁰ Depending on their coverage plan and the type of ONET service they received, members might be financially responsible for the difference between the UCR rate and the provider’s billed charge.¹¹

25. I understand that certain health plan sponsors may specify the data source and level that is used to pay ONET claims. I also understand that, during the class period, the data source used most frequently by Aetna as the basis for determining the UCR rate was the Ingenix Database, although the percentiles of the Ingenix Database used to pay ONET claims varied.¹² I also understand that even when Aetna used the Ingenix Database as a benchmark to pay ONET claims, it would still vary the amount it paid to ONET providers for reasons such as the use of a modifier on the claim. Thus, my analysis in this report focuses on purely the output of the Ingenix Database compared to certain benchmarks. My analysis does not address in any way how Aetna used the unmodified output of the Ingenix Database to pay ONET claims during the class period.

26. The company known as Ingenix, which is a wholly-owned subsidiary of UHG,¹³ produces provider charge data in two different databases: (a) the PHCS; and (b) the Medical Data Research (“MDR”) databases.¹⁴ Ingenix obtained PHCS from the Health Insurance Association of America (“HIAA”) in October 1998 and MDR through Ingenix’s purchase of Medicode, Inc. in December 1997.¹⁵ When Ingenix obtained PHCS and MDR, it allegedly merged the underlying data.¹⁶

⁷ See Complaint at ¶ 3. I understand that in-network providers are reimbursed for services at rates negotiated between the provider and a managed care company, whereas out-of-network providers do not have contracts with negotiated rates.

⁸ See Complaint at ¶ 1.

⁹ See Complaint at ¶ 4.

¹⁰ See *Ibid.*

¹¹ See Complaint at ¶ 22. I understand in this regard that different plans establish the UCR rate at different percentile levels of comparable physician charges. *See, e.g.*, Deposition Transcript of James Cross (Mar. 23, 2010) at p. 89. I also understand that the UCR rate is most frequently established by Aetna plans at the 80th percentile of physician charges. *See AET-C00103216-7.*

¹² *See, e.g.*, AET-C00103216-7; and Aetna, Inc. 2009. “Important health and health benefits information,” available at www.aetna.com/data/disclosures/Medical_aetna_pays_oon_benefits.pdf (last visited Apr. 5, 2010).

¹³ See Complaint at ¶ 6

¹⁴ See Complaint at ¶ 30.

¹⁵ See Complaint at ¶ 132.

¹⁶ See Complaint at ¶ 147.

27. I understand that the Ingenix Database (a) accepts claims information from numerous large managed care companies, including Aetna;¹⁷ (b) aggregates this information; and (c) sells a set of data showing distributions of provider charges¹⁸ organized by reference to statistical parameters such as particular percentile values.
28. Plaintiffs allege that the data collection arrangement between Ingenix and large managed care companies is the “conduit of the conspiracy.”¹⁹ Plaintiffs further allege that “an inherent and irreconcilable conflict of interest” faces managed care companies that both contribute data to and rely on the Ingenix Database in determining UCR rates.²⁰ Plaintiffs allege that the inherent conflict of interest of the arrangement has resulted in a flawed and biased methodology in the data contribution and processing of values for the Ingenix Database. Moreover, they allege that this flawed methodology causes a systematic material difference between the Ingenix Database-reported values and the “true” values for provider charges, which allegedly leads to class-wide under reimbursement for ONET services:

Aetna’s wrongful conduct affects hundreds of thousands of consumers nationwide who have had to pay more for ONET services as a result of Aetna’s illegal agreement, and it affects hundreds of thousands of Providers who have been paid less for ONET. . . . Aetna contracted with Ingenix to provide ONET data claims and receive uniform pricing schedules which are used to calculate reimbursements for ONET services at artificially low rates (herein “False UCRs”) that are presented as UCRs but are, in fact, substantially below the actual UCR.²¹

29. Prior to the consolidation of the instant litigation, there have been few investigations and reviews by courts of the allegations and concerns about the Ingenix Database methodology.²² Of those few evaluations, I do not have sufficient information to comment on all of the analyses and results. However, in each that I am aware of, a consistently presented view is that the alleged flaws in the methodology for data contribution and processing of the values in the Ingenix Database result in a systematic downward bias of the reported percentiles typically used to calculate UCR rates for

¹⁷ Dr. Siskin states there are “20, 25 major companies” that are contributors. *See Transcript of Proceedings (Siskin), Wachtel v. Guardian Life, et al., McCoy v. Health Net, Inc., et al.* (Apr. 10, 2008) (the “Siskin Transcript”) at p. 14. Ingenix management states there are “approximately 100 major contributors in 50 states.” *See Slavitt, A. and D. Ostler. 2008. “In defense of data: UnitedHealth Group’s Ingenix, says data collection unbiased, makes system better,” Modern Healthcare*, Feb 25.

¹⁸ *See* Complaint at ¶¶ 6-7.

¹⁹ *See* Complaint at ¶ 7.

²⁰ *See* Complaint at ¶ 8.

²¹ *See* Complaint at ¶ 6. I note that the term “uniform pricing schedules” is Plaintiffs’ term, and I neither accept nor endorse its use.

²² *See, e.g.,* Opinion, McCoy v. Health Net, Inc., et al., Wachtel, et al. v. Health Net, Inc., et al., and Scharfman, et al. v. Health Net, Inc., et al. (D.N.J. filed Aug. 8, 2008); NYAG Report; U.S. Senate Committee on Commerce, Science, and Transportation, “Underpayments to Consumers by the Health Insurance Industry,” Staff Report for Chairman Rockefeller (Jun. 24, 2009) (the “Rockefeller Report”); First Amended Class Action Complaint, Weintraub v. Ingenix, Inc. et al., Case No. 08-CV-00654 (MRK) (Aug. 15, 2008); Third Amended Class Action Complaint, Cooper et al. v. Aetna Health Inc. PA, Corp. et al., Case No. 07-CV-03541(FSH)(PS) (D.N.J. filed Feb. 28, 2008); and the Complaint.

ONET services. My review of the materials available to me regarding these prior studies, however, calls into question the rigor of the empirical analysis conducted to support such a definite conclusion. As one example, my analysis addresses the frequently cited study prepared by the Attorney General of New York. I report below that when subjected to a standard investigation of the generality of its results, that study's conclusions are not supported by an empirical analysis of publicly available data.

2. Statistical and Economic Analyses Related to Common Proof of Impact

30. Statistical and economic evidence often is relevant to whether or not a common proof of impact exists because such evidence might support or refute the homogeneity of the class characteristics, injuries, or both. In addition, statistical and economic evidence is used to test for the presence of individualized factors that would challenge the existence of a generalized proof. My assignment in this matter involves assessing whether there is a common formula, model, or other methodology that Plaintiffs could use to establish that each class member suffered injury in a directionally consistent way and that damages can be measured reliably using a formulaic approach.²³ In the instant matter, Plaintiffs contend that the alleged injuries and damages are linked to the "flawed uniform pricing schedules (effectively UCR rates) that systematically result in the under-reimbursement for ONET."²⁴ Plaintiffs contend that a common issue in this litigation is "[w]hether Aetna's use of the Ingenix database itself resulted in lower UCR determinations than were otherwise available based on appropriate information."²⁵ Economic and statistical information can be examined to test whether both a common class-wide proof of these alleged impacts and a reliable, formulaic method to measure the damages are available to Plaintiffs.
31. In addition, due to the specific allegations regarding the challenged conduct, economic and statistical analysis might reveal issues or ensuing results over which the interests of substantial portions of the purported classes are in fundamental conflict. Regarding the methodology to construct the distribution of values in the Ingenix Database, I consider and test the existence of such fundamental conflicts of interests among members of the proposed classes. Specifically, I address whether fundamental antagonistic interests are present among the proposed class members due to Plaintiffs' basic theory of how flaws in the Ingenix Database methodology for data contribution and processing resulted in allegedly biased values for ONET services.

B. Plaintiffs' Theory of "Core Concepts" Likely Results in Antagonistic Interests among Members of the Proposed Classes

32. According to Plaintiffs' allegations, the Ingenix Database uses four fields of information to construct a distribution of values by Current Procedural Terminology ("CPT") or

²³ This is the often cited "common proof of impact" issue in economic studies related to class certification. See, e.g., Johnson, J.G. and G.K. Leonard. 2007. "Economics and the Rigorous Analysis of Class Certification in Antitrust Cases," *Journal of Competition Law and Economics*, 3(3): pp. 341–356.

²⁴ See Complaint at ¶ 180.

²⁵ See Complaint at ¶ 566 (d).

Current Dental Terminology (“CDT”) and geozip or “geozip grouping.”²⁶ These fields are (a) date of service; (b) 5-digit CPT (or CDT) code; (c) the zip code where the procedure was performed; and (d) the amount of the provider’s billed charge.²⁷

33. In a hearing held by the Court in the *Health Net* matter, testimony was given by Dr. Bernard Siskin about the implications of using only four data fields to construct and compile the Ingenix Database.²⁸ The Court has stated that “[t]he question addressed during the Court’s April 10th hearing was whether these databases satisfied two ‘core concepts’ of UCR. That is, whether the Ingenix databases provided accurate data as to the reasonable charge for a particular service, and the geographic area where the service was performed.”²⁹
34. As I understand Plaintiffs’ arguments and the reported opinions of Dr. Siskin,³⁰ they each contend that reliance on just these four data fields will result in distributions of values that generalize or aggregate across material distinguishing features of the charges, across medical market areas, or both. Plaintiffs contend that such aggregation causes certain charges to exceed the calculated UCR incorrectly and violates the “core concepts” of UCR:

These four data points exclude several factors that are critical to the “core concepts” of UCR. These four data points do not identify: (1) the provider’s licensure or qualifications; (2) the patient’s age or health status; or (3) the type of facility where the procedure was performed. The database does not take into account whether a particular procedure was performed by a highly skilled Board Certified specialist or a general practitioner or a paraprofessional or a nurse. . . . [B]y including every possible type of provider in the CPT Code Service, even a totally average bill from a skilled physician will be higher than the UCR yielded by the database. Ingenix’s failure to control for these factors means that the database is not actually comparing similarly situated procedures when it purportedly yields a “usual” and “customary” rate for that procedure.³¹

²⁶ A “geozip grouping” is a collection of geozips for which there is one distribution of values for all of the included geozips. I note that in this report, I use “geozips grouping” and “geozips record” interchangeably.

²⁷ See Complaint at ¶ 155.

²⁸ See Siskin Transcript.

²⁹ See Opinion, McCoy v. Health Net, Inc., et al., Wachtel, et al. v. Health Net, Inc., et al., and Scharfman, et al. v. Health Net, Inc., et al. (D.N.J. filed Aug. 8, 2008) at p.26.

³⁰ See Expert Report of Bernard R. Siskin, Ph.D., Wachtel v. Health Net, McCoy v. Health Net (Mar. 31, 2004) (the “Siskin Report”) at pp. 3-4.

³¹ See Plaintiff Carolyn Whittington’s Response to Aetna Defendants’ Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010) (the “Whittington Interrogatory”) at pp. 5-6. Accord Plaintiff Angela Hull’s Responses and Objections to Aetna’s Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 13, 2010); Plaintiff Carolyn Samit’s Response to Aetna Defendants’ Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010); Plaintiff Carolyn Whittington’s Response to Aetna Defendants’ Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010); Plaintiff Darlery Franco’s Response to Aetna Defendants’ Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010); Plaintiff Jeffrey M. Weintraub’s Responses and Objections to Aetna’s Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 13, 2010); Plaintiff Michele Cooper’s Response to Aetna Defendants’ Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010); Plaintiff Michele Werner’s Response to Aetna Defendants’ Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010); Plaintiff Paul and Sharon Smith’s Response to Aetna

35. A critical assumption in the instant matter and the prior investigations is that separating the data of the existing distributions to produce “similarly situated” conditions will indicate higher UCR values for the purported classes. It cannot be presumed, however, that separation of the existing distributions would result in higher upper percentile values for all or nearly all Plaintiffs. In fact, given the degree of aggregation described by Plaintiffs and the large number of contributors to the Ingenix Database, it is highly likely that many distributions would have lower values for the upper percentiles if the charges were separated as suggested by Plaintiffs. Consequently, in Plaintiffs’ proposed “but-for” world, many separated distributions would imply lower UCR rates for substantial proportions of members of the purported classes.
36. This fundamental property of disaggregating pooled data can be illustrated easily with Figure 1. The figure shows three distributions for a single CPT code. The lower distribution reflects lower charges, perhaps due to a lower level of the providers’ qualifications as Plaintiffs allege.³² The upper distribution reflects higher charges and higher qualifications. The pooled distribution ignores the qualifications. Persons who exceeded the UCR_p but were in the upper distribution (i.e., to the right of UCR_p but in $Distribution_U$) might have been under reimbursed as Plaintiffs allege and as Dr. Siskin has opined:

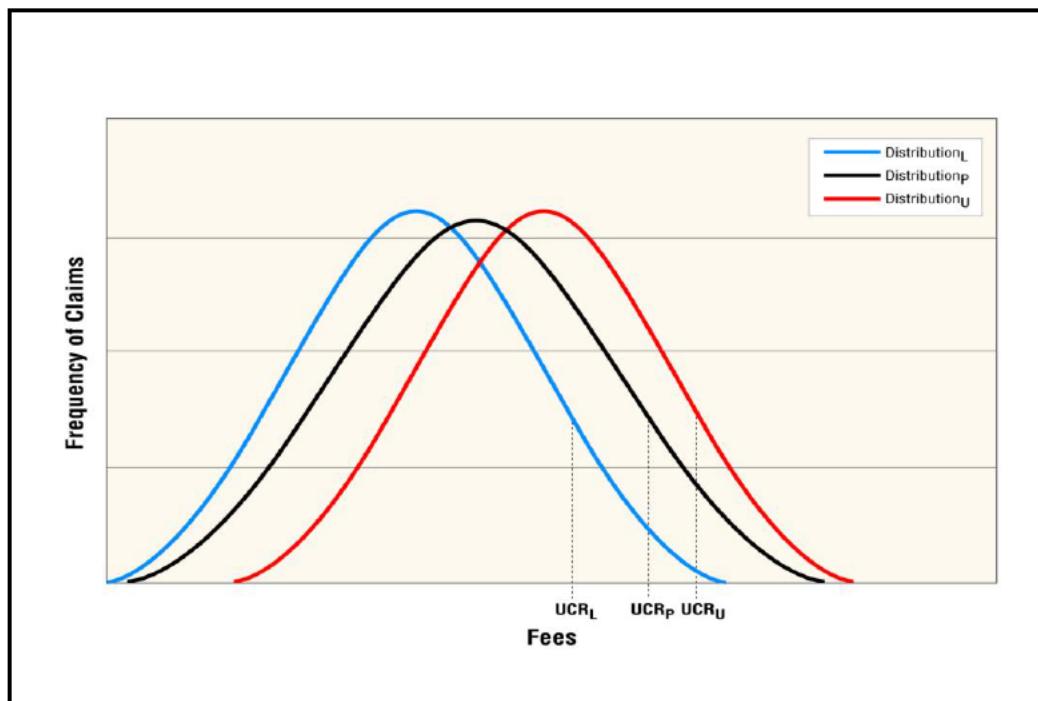
If two unlike distributions of similarly situated charges are combined, the methodological flaw of combining like and unlike charges in establishing UCR for a “particular” service results in all those in the higher price distribution who are affected by a UCR calculation receiving less than they should. In every case, combining unlike charges to establish UCR causes those persons from the higher distribution for that “particular” service to receive less than they should.³³

Defendants’ Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010); and Plaintiffs’ Objections and Responses to Aetna’s Second Set of Interrogatories to Provider Plaintiffs, In Re: Aetna UCR Litigation (Jan. 13, 2010) (collectively, “Plaintiffs’ Collective Responses to Aetna’s Second Set of Interrogatories”). I note that the statements contained in Plaintiffs’ Collective Responses to Aetna’s Second Set of Interrogatories are substantially similar across the individual interrogatory filings. For the purposes of brevity, I specifically cite to the Whittington Interrogatory.

³² By using this example, I am neither accepting nor endorsing Plaintiffs’ contention that physician qualifications are a reason to disaggregate CPT charge distributions.

³³ See Siskin Report at p. 10.

Figure 1: Examples of Distributions for Pooled and Disaggregated Data



37. What Plaintiffs and Dr. Siskin do not address is the implication for the lower population of separating the distributions. If there is a material effect on the upper population from separating the charges, there also must be an effect on the lower distribution. This effect is to *lower* UCR_P for the lower distribution to UCR_L. In the actual world, persons in the lower distribution with charges above UCR_L benefit from the effects of pooling with higher value distributions. This is a basic result of pooling data across populations.
38. Assuming as true Plaintiffs' allegation that the Ingenix Database reflects pooled distributions that do not separate charges based on the factors suggested by Plaintiffs, members of the purported classes do not all have a common interest in proving that the alleged use of pooled distributions was unlawful. In fact, the interests of proposed class members in the upper distributions are directly and fundamentally in conflict with the interests of proposed class members in the lower distributions. Situations for which this would not be true would be when there are no differences in the distributions—a result that would lead to no harm under Plaintiffs' theory—or when all data from the upper distribution have been removed from the Ingenix Database prior to publication of the pricing distributions.³⁴ The latter case is unlikely given the number of contributors and

³⁴ I note in this regard that during Dr. Siskin's testimony in the April 10, 2008 hearing, the Court apparently was given the impression that "the way that the data was scrubbed effectively removed the second of the two bimodal distributions." See Siskin Transcript at p. 59. As Plaintiffs acknowledge, for most of the subject period Aetna only contributed about 17 percent of the data to the Ingenix Database. See Whittington Interrogatory at p. 18. Accord Plaintiffs' Collective Responses to Aetna's Second Set of Interrogatories. Even if Plaintiffs were to demonstrate that Aetna scrubbing procedures resulted in removal of all of the upper distribution data contributed to Ingenix by Aetna, Plaintiffs also would have to demonstrate that the scrubbing processes of all the other Contributors and Ingenix led to the removal of all upper distribution data.

the extensive pooling that has apparently occurred to construct the distributions, and I am not aware of allegations that such a case actually occurred.

C. Readily Available Benchmarks Exist to Test Common Proof of Impact

39. If the data contribution and processing methodology for the Ingenix Database resulted in “lower UCR determinations than were otherwise available based on appropriate information,” then an obvious approach to assessing the availability of class-wide proof of common impact is to seek a readily available source of appropriate data. Economic damages are typically measured by reference to some description of a hypothetical world that would have existed but for the presence of the alleged unlawful behavior – often referred to as a “but-for” world. The investigation of impact is made by reference to one or more defensible benchmarks selected to be free of the challenged conduct.³⁵ In my review of industry information, I found that such data benchmarks do exist, at least with respect to the challenged conduct regarding the “inherent and irreconcilable conflict of interest” and conspiracy allegations.
40. Table 1 lists a number of databases for benchmark fee information. Other than the last source, these are commercial products sold in standard outlets for the healthcare industry. Importantly, some of these products are based on data collected directly from physicians and other contributors not subject to the conflict of interest allegations made by Plaintiffs in this matter. I review the coverage, availability, and use of these products below and Appendix A contains details about the acquisition and compilation of all the datasets used in my analysis.
41. The last product in the table is a government database that healthcare consultants cite as a reliable source for healthcare fee setting and analysis.³⁶ Although it does not provide percentile values, average charge values can be calculated from the data. Obviously, these data are free of the alleged conspiracy claims made by Plaintiffs.

³⁵ I use the term “benchmark” to refer generally to a standard for UCR levels in the hypothetical world that is free of the alleged unlawful conduct. I note that Plaintiffs have identified the “out-of-network health care cost database being developed by FAIR Health, Inc. under the auspices of Syracuse University, State University of New York (“SUNY”) at Buffalo, University of Rochester, and SUNY Upstate Medical University” in response to an interrogatory about how the UCR should be determined. See Whittington Interrogatory at pp. 2-3. Accord Plaintiffs’ Collective Responses to Aetna’s Second Set of Interrogatories. As information about this database currently is not available to me, I cannot comment on its correspondence to the Ingenix Database values or the other available commercial and government benchmarks. I therefore reserve the right to consider the FAIR Health Database in the context of my analysis and opinions if and when it becomes available to me.

³⁶ See, e.g., American Medical News. 2009. “How to set your fee schedule: Experts advise updating it every 3 to 12 months,” available at www.ama-assn.org/amednews/2009/05/04/bisa0504.htm (last visited Mar. 22, 2010).

Table 1: Providers of Benchmark Fees

Benchmark (“Short Name”)	Publisher	Values Provided	Source and Volume of Data
Medical Fees in the United States (“PMIC”)	Practice Management Information Corporation, Inc.	50th, 75th, and 90th percentiles	“More than 400 million” claims from “service bureaus, group practices, clinics, universities, and practice management system vendors are among the many types of organizations that supplied the claims data utilized for fee schedule development.” ¹
Physicians Fee Reference (“PFR”)	Yale Wasserman, D.M.D. Medical Publishers, Ltd.	50th, 75th, and 90th percentiles	“Fee information contained in the PFR is based primarily on the results of our annual independent direct mail confidential survey which was conducted in the fourth quarter of 2005. Survey participants included physicians, group practices, office managers, medical billing services, clinics, universities, hospitals, health care administrators and medical practice management consultants. Secondary sources included purchased data from claims clearinghouses.” ² Does not specify volume of data.
National Dental Advisory Service Comprehensive Fee Report (“NDAS”)	Yale Wasserman, D.M.D. Medical Publishers, Ltd.	40th, 50th, 60th, 70th, 80th, 90th, and 95th percentiles	“Fee information contained in this report is the result of a statistical analysis of confidential NDAS fee surveys.” ³ Does not specify volume of data.
Physicians Fee & Coding Guide (“MAG”)	MAG Mutual Healthcare Solutions, Inc.	Low and high	“The data used to establish the \$FEE RANGE is from a variety of sources including actual physicians' charges, health insurer's databases and an extensive analysis of insurers' Explanation of Benefits to determine their allowables.” ⁴ Does not specify volume of data.
Physician/Supplier Procedure Summary Master File (“Medicare PSPS”)	Centers for Medicare and Medicaid Services	Total claims and dollars charged	“This file is a 100% summary of all Part B Carrier and [Durable Medical Equipment Regional Carrier] Claims processed through the Common Working File and stored in the National Claims History Repository. The file is arrayed by carrier, pricing locality, Healthcare Common Procedure Coding (HCPC), modifier 1, modifier 2, specialty, type of service and place of service. The summarized fields are total submitted services and charges, total allowed services and charges, total denied services and charges, and total payment amounts.” ⁵

Notes:

1. See Practice Management Information Corporation. 2005. *Medical Fees in the United States 2005*. Los Angeles, CA: Practice Management Information Corporation at p. 2.
2. See Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2006. *Physicians' Fee Reference 2006*. Milwaukee, WI: Yale Wasserman, D.M.D. Medical Publishers, Ltd. at p. 1.
3. See Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2007. *The Original National Dental Advisory Service 2007*. Milwaukee, WI: Yale Wasserman, D.M.D. Medical Publishers, Ltd. at p. 1.
4. See MAG Mutual. 2007. *2008 Physicians Fee & Coding Guide*. Duluth, GA: MAG Mutual Healthcare Solutions, Inc. at p. ix.
5. See Centers for Medicare & Medicaid Services. 2009. “Physician/Supplier Procedure Summary Master File,” available at http://www.cms.hhs.gov/NonIdentifiableDataFiles/06_PhysicianSupplierProcedureSummaryMasterFile.asp (last visited Mar. 10, 2010).

1. Product and Geographic Market Segments

42. Consideration of the type of analysis necessary to demonstrate common impact in this matter must recognize that the subject products cover thousands of procedures in potentially hundreds or thousands of “genuine medical market[s]”³⁷ or “medical service areas amendable [sic] to cost comparison.”³⁸ This is a far more challenging definitional and measurement problem than one in which a single, relatively homogeneous good is sold in well-understood product and geographic markets. As I understand Plaintiffs’ claims, they do not believe that (a) even the nearly 9,000 five-digit CPT codes are sufficient to characterize the product market segments for procedures; and (b) the approximately 400 geozip areas³⁹ are sufficient to characterize the geographic market segments.

³⁷ See Whittington Interrogatory at p. 9. *Accord* Plaintiffs’ Collective Responses to Aetna’s Second Set of Interrogatories.

³⁸ See Complaint at ¶ 167.

³⁹ As Plaintiffs have noted, Ingenix groups some geozips together for the pricing data resulting in a unique geozip

43. Implementation of the highly disaggregated approach that Plaintiffs seek is likely to require claim- and claimant-specific details for perhaps millions of cases. For example, as the Rockefeller Report demonstrated in the example of Jill Faddis, some consumers might insist that patient origin and information from their individually specific Yellow Pages become the determinants of their geographic market.⁴⁰ Such detail not only renders a common proof of impact unlikely but also further exacerbates the low claim count problem that subsequently gives rise to the need for derived values.⁴¹
44. In contrast, we have direct industry evidence on how commercial publishers and the government have solved market segmentation issues. Details about the segmentation in the various data sources are described below, but to summarize, product market segments for charge data look similar to those used in the Ingenix Database. Outside of the Medicare PSPS benchmark, there is apparently very little further refinement of the CPT or CDT service description to pool charge data.⁴² Geographic segments vary from idiosyncratic market designations (MAG) to segmentation by CMS regions⁴³ (PMIC and Medicare PSPS). Similar to Ingenix, two of the four commercial products use a geozip segmentation (PFR and NDAS).
45. The existence of these alternative databases challenges one of Plaintiffs' maintained hypotheses in this matter. Plaintiffs hypothesize that information about providers' charge value and distributions is not readily available. As noted, my review easily identified these products. In the context of common impact, these data products produced in the ordinary course of business are obvious sources of information to benchmark the Ingenix Database values and test for evidence of a common downward bias.

2. Commercial and Government Databases Are Valid Benchmarks

46. My review of industry information and websites indicated that the benchmark databases are readily available and routinely referenced in third party analysis. Table 2 shows information from selected healthcare industry websites referencing the benchmarks or listing the benchmark database products for sale. All of the commercial benchmark products also are easily found and can be purchased from Amazon.com.

record count less than the approximately 900 geozips in the U.S.

⁴⁰ See Rockefeller Report at p. 9 and Exhibit C.

⁴¹ "Derived values" are given if there are fewer than nine occurrences for a procedure in one geozip. These charges "use a blended methodology of a relative value scale and charge data in determining conversion factors to be used in calculating benchmarking amounts." See AET-00297112.

⁴² I understand that healthcare payers might separately consider CPT "modifiers" as submitted in the insurance coverage documentation. A modifier "provides the means to support or indicate that a service or procedure that has been performed has been altered by some specific circumstance but not changed in its definition or code." See American Medical Association. 2009. *CPT 2009 Professional Edition*. Chicago, IL: American Medical Association at p. xv. My observation refers to the commercial databases as published.

⁴³ I use "CMS region" generally to refer to payment localities identified in the Geographic Practice Cost Index as defined by the Centers for Medicare & Medicaid Services. See Acumen LLC, "Review of Alternative GPCI Payment Locality Structures" (Jul. 28, 2008).

Table 2: Illustrative Benchmark References and Availability for Purchase

PMIC	MAG	PFR
A & R Medical Billing, Inc. ¹	AMA Bookstore ⁸	MedeTrac ¹⁰
Acupuncture Today ²	ChiroWeb ⁹	SuperCoder ¹¹
Chiropractic Economics ³	Medical Arts Press ⁵	
Ethical Health Partnerships ⁴		
Medical Arts Press ⁵		
Practice Support Resources ⁶		
Pam Pohly's Net Guide ⁷		

Notes:

1. See A & R Medical Billing, Inc. 2005. "Setting Your Professional Fees," available at www.armedicalbilling.com/ARNEWSLETTERWEBDECEMBER2005.pdf (last visited Mar. 15, 2010).
2. See Collins, S.A. 2008. "Fee Schedules and Charges," available at atpracticeinsights.com/mpacms/at/article.php?id=31819 (last visited Mar. 15, 2010).
3. See Kotlar, M. 2008. "'Usual and customary' Aim for a reasonable but competitive fee structure," available at www.chiroeco.com/chiropractic/news/4139/871/'Usual-and-customary-Aim-for-a-reasonable-but-competitive-fee-structure/ (last visited Mar. 9, 2010).
4. See Liphrott, D.J. 2005. "Does Your Doctor Charge Too Much?" available at www.ethicalhealthpartnerships.org/doctorfees.html (last visited Mar. 15, 2010).
5. See Medical Arts Press. "Fee Calculators – Code Books | Coding & Billing," available at www.medicalartspress.com/fee-calculators-code-books/cbl/8099.html (last visited Mar. 9, 2010).
6. See Practice Support Resources, Inc. 2010. "Practice Support Resources, Inc.: Medical Fees/Charges," available at www.practicesupport.com/Merchant5/merchant.mvc?Screen=CTGY&Store_Code=PSR&Category_Code=FS (last visited Mar. 9, 2010).
7. See Pam Pohly's Net Guide. "Healthcare Finance, Accounting, Economics & Reimbursement Resources," available at www.pohly.com/admin_financial.html (last visited Mar. 15, 2010).
8. See AMABookstore.com. 2010. "Reimbursement Products," available at www.amabookstore.com (last visited Mar. 9, 2010).
9. See Murkowski, K.S.J. 2010. "CPT Confusion, Part I," available at www.chiroweb.com/mpacms/dc/article.php?id=38183 (last visited Mar. 15, 2010).
10. See MedeTrac Systems L.L.C. 2010. "Physicians Fees & Benchmarking Books from AMA, Ingenix, Wasserman -More -MedeTrac," available at www.medetrac.com/products.asp?cat=865 (last visited Mar. 9, 2010).
11. See Tuck, R.H. 2000. "Point of View: Enhance Your Revenue by Reviewing 10 Key Procedures," available at www.supercoder.com (last visited Mar. 15, 2010).

47. In addition, there is other information that indicates that the commercial products are recognized as benchmarks in the industry. PFR has been used as a benchmark in other court proceedings.⁴⁴ These benchmarks also are used by industry associations in their agreements with insurers.⁴⁵
48. Table 3 is a listing of various well-recognized health science journals that published articles relying on the benchmark products. At my direction, Exponent staff conducted an illustrative analysis of the potential awareness of health scientists regarding the commercial products. This review revealed dozens of such articles that cited the commercial benchmarks.

⁴⁴ See In Re Adoption of N.J.A.C. 11:3-29 by the State of New Jersey, Department of Banking and Insurance, No. A-0344-07T3 (N.J. Super. Ct. App. Div. filed Aug. 10, 2009).

⁴⁵ Apparently PFR was used by the Physicians Medical Group of San Jose as part of a claim delegation agreement with Aetna. See, e.g. AET-03582589-98. MAG also has been used for such purposes. See, e.g., AET-035822477-86.

Table 3: Illustrative Health Science References to the Commercial Products

High-Impact¹ Journals With At Least One Citation to One Benchmark	No. Articles Referencing Each Benchmark²
<i>American Journal of Cardiology</i>	22 articles referencing PMIC
<i>American Journal of Psychiatry</i>	29 articles referencing PFR
<i>Annals of Internal Medicine</i>	42 articles referencing MAG
<i>Archives of Internal Medicine</i>	
<i>Arthritis & Rheumatism</i>	
<i>Cancer</i>	
<i>Clinical Infectious Diseases</i>	
<i>Diabetes Care</i>	
<i>Gastroenterology</i>	
<i>Journal of the American Medical Association</i>	
<i>Pediatrics</i>	

Notes:

1. High impact based on the Thompson Reuters “Impact Factor,” a “measure of the frequency with which the average article in a journal has been cited in a particular year or period.” See Thompson Reuters. 2010. “Introducing the Impact Factor,” available at thomsonreuters.com/products_services/science/academic/impact_factor/ (last visited Mar. 17, 2010).
2. Scientific literature web search based on keywords conducted over the period from January to March 2009.

a) Product Segmentation

- 49. Although existing benchmarks vary in their methods to segment the product and geographic markets, none approaches the level of segmentation promoted by Plaintiffs. All benchmarks use some variation of CPT or CDT codes to segment services.
- 50. The Medicare PSPS contains information on claim count that can be used to investigate the frequency patterns of CPT codes and to address the number of codes that typically account for the vast majority of the claims. Table 4 presents an analysis of the frequently used CPT codes. The data show that approximately 93 percent of the 1.5 billion claims are attributed to 500 CPT codes.⁴⁶ This analysis suggests that there is little need for yet more segmentation in the current method employed by Ingenix which primarily uses CPT codes for product segmentation.

⁴⁶ I also conducted the same analysis on the 2006 Ingenix Database and found that the top 500 CPTs accounted for 94 percent of the empirical medical and surgical claims.

Table 4: Cumulative Claim Frequency of the Top CPTs

CPT-Code Ranking by No. Claims	% of All CPT Codes	No. Corresponding Claims	% of All Claims
Top 5	0.06%	335,825,232	22%
Top 10	0.12%	462,916,558	30%
Top 15	0.17%	565,546,017	37%
Top 20	0.23%	642,518,043	42%
Top 25	0.29%	699,151,335	46%
Top 50	0.58%	878,143,655	57%
Top 100	1.16%	1,067,556,763	70%
Top 200	2.32%	1,248,925,556	82%
Top 500	5.81%	1,425,148,047	93%

Note:

1. There were 8,607 distinct CPT codes among submitted Part B claims in 2006 including modified CPTs (not including Level II HCPCS codes).
2. There were 1.53 billion claims in 2006.

Source: Medicare PSPS data, 2006.

51. Some benchmarks adjust charge values or further disaggregate charge data using modifier codes. Table 5 shows the number of procedures in each database, and the number of procedures to which modifiers were applied in 2006. Only Medicare PSPS uses modifiers extensively to separate the charge data.⁴⁷

Table 5: Use of Modifiers in the Benchmark Databases

Benchmark	No. CPT/CDTs in Dataset	No. Modifiers in Dataset
MAG	8,256	3
Medicare PSPS	8,396*	955
NDAS	561	0
PFR	8,256	1
PMIC	8,256	1

Notes:

* Excludes modified CPTs.

52. There are 955 modifiers applied to CPT codes in the 2006 Medicare PSPS data. The claims data are organized separately for each modified CPT service. As a result, I am able to investigate the implications of using modifiers by comparing average charges for modified and unmodified claims for the same CPT service. My analysis uses a standard method of comparison by creating “matched pairs.” A matched pair is made by comparing the average charge for a specific CPT in a geographic area (unmodified) with the average charge that is calculated using the claim data that has been adjusted by a specific modifier (modified) for the same CPT in the same geographic area.

⁴⁷ I also understand that managed care companies often use the Ingenix Database values as a basis to determine “base-case” UCRs. Further adjustments are then often made for modifiers and other plan factors to determine reimbursement. See, e.g., Aetna, Inc. 2009. “Important health and health benefits information,” available at www.aetna.com/data/disclosures/Medical_aetna_pays_oon_benefits.pdf (last visited Apr. 5, 2010).

53. For my analysis, I distinguish the proportion of matched pairs for which the modified and unmodified average charge are the same (i.e., the modifier does not affect the average charge); the modified average charge exceeds the unmodified average charge (Modified > Unmodified); and the modified average charge is less than the unmodified average charge (Modified < Unmodified). The results for these categories are shown in Table 6. The last row of the table shows that when modified claims are compared to unmodified claims, the application of the modifier reduces the average charge amount in more than 58 percent of the cases. Importantly, this analysis applies to a large number of Medicare PSPS claims as shown in the table. Based on the matched pairs, my analysis suggests that if Ingenix were to include all charge data with modifiers in constructing the distributions of charge data it would be more likely to *reduce* UCR values than to *increase* them. Importantly, there is no common effect from the application of modifiers. In addition, Plaintiffs' promotion of the use of modifiers is another likely source of antagonistic interests among class members. Some members may gain from the application of modifiers, but others would face lower values for the upper percentiles in Plaintiffs' proposed but-for world.

Table 6: Comparison of Non-Modifier and Modifier Average Charge from Medicare PSPS Data, 2006

Result	Count of Matched Pairs ¹	Percent	No. Claims	
			Modified	Unmodified
No Effect on Average Charge	7,092	2%	62,830	302,483
Modified > Unmodified	144,006	40%	164,259,076	408,160,265
Modified < Unmodified	211,276	58%	381,476,755	548,282,656

Notes:
 1. "Count" indicates the number of matched pairs between an unmodified CPT-by-CMS region and a modified CPT-by-CMS region.

54. Based on the Medicare PSPS results, the evidence does not support the allegation that the inclusion of charge data with modifiers would increase charge values across the board. I therefore restricted my analysis to the unmodified CPT or CDT services in the Ingenix Database in selected system codes which I discuss below. This subset of the data covers more than half of the claim count in the Ingenix data for each year examined. As a result, the subset represents a sufficiently large foundation to investigate whether substantial conflicts exist among members of the proposed classes and to test the hypothesis of common impact.

b) Geographic Segmentation

55. Table 7 shows the geographic organization for the benchmarks, further described in Appendix B. Only MAG contains idiosyncratic definitions of geographic areas—listing over 400 named geographic regions. The other benchmarks use the CMS region or a static geozip definition to segment geographic markets.

Table 7: Geographic Organization of Fees by Benchmark

Benchmark	Geozip	MAG Region	CMS Region
MAG		✓	
Medicare PSPS			✓
NDAS	✓		
PFR	✓		
PMIC			✓

- 56. Due to the variation in the geographic organization across the databases, my analysis requires a “mapping” from each benchmark to the geozip areas used in the Ingenix Database. Appendix B describes my methodology for the mappings. Importantly, I am able to make direct comparisons to a substantial portion of the CMS regions in the PMIC and Medicare PSPS databases and to all of the geozips in the PFR and NDAS databases without the need for additional assumptions about the correct geographical mapping.
- 57. PFR reports geographic adjustment factors for every geozip. Although this is a static measure of the “genuine medical market,” it is more disaggregated than the grouped geozip records in the Ingenix Database. Plaintiffs claim that geozip grouping “may further skew the data.”⁴⁸ I test below whether the higher level aggregation in the Ingenix Database distributions causes the Ingenix values to be lower than the matched PFR values.
- 58. In addition, the MAG database is useful for testing directly whether Ingenix Database values are skewed because they are geographically referenced to static geozips as opposed to some other geographic designation that might change with market conditions. In its documentation, MAG indicates that the determination of geographic adjustment factors (“GAFs”) for the charge data is made with reference to the type of market information that Plaintiffs contend is ignored by static geographic locations:

[The included documentation] provides a mechanism for refining the fee information in this guide to specific geographic areas. The Geographic Adjustment Factors included in this appendix *are based upon an analysis of fees in various areas and government studies of variations in economic factors among localities. . . .* The adjustment factors provided within are not directly comparable to Medicare’s Geographic Adjustment Factors because Medicare’s scheme provides only a token recognition of the variation in cost-of-living among localities.⁴⁹

- 59. I note that with the exception of the Medicare PSPS database, the existing benchmarks apply a single GAF to every CPT or CDT code in a geographic area. Thus, although these benchmarks might address the segmentation of the geographic area with more “detail” than Ingenix, they offer potentially less variation in charge detail for the product segmentation. In each case, the geographic markets are defined in the same way for all

⁴⁸ See Whittington Interrogatory at p. 9. *Accord* Plaintiffs’ Collective Responses to Aetna’s Second Set of Interrogatories.

⁴⁹ See MAG Mutual. 2004. *2005 Physicians Fee & Coding Guide*. Duluth, GA: MAG Mutual Healthcare Solutions, Inc. at Appendix B. (Emphasis added.)

procedure codes in the database – that is, the commercial databases do not define different geographic markets for different procedure codes.

3. Scope and Coverage of the Benchmark Analysis

60. Table 8 indicates the Ingenix data modules that I received from Counsel and the years that I investigated for my analysis.⁵⁰ The years selected were a result of the data readily available from the benchmarks. All benchmarks were available for 2006. Some commercial benchmarks—PMIC and MAG—were available for 2005. I also examined a portion of the data for 2007 to compare it with the analysis performed in the NYAG Report.

Table 8: Summary of Ingenix Modules Analyzed

Surgical	Medical	Dental
2001	2001	
2002	2002	2002
2003	2003	2003
2004	2004	2004
2005	2005	2005
2006	2006	
2007	2007	2006
2008	2008	2007

Notes:

1. Listed years represent data received.
2. Enclosed highlighted years represent data used in the analysis.

61. Table 9 shows that in year 2006, the output from the Ingenix Database represents data from more than a billion claims. For the various reasons detailed in Appendix A, I conducted my comparative analysis on the empirical fees for medical and surgical modules only—shown in the last row of table. These claims were approximately 61 percent of the total claims. Moreover, the potential value of these claims is substantial. In terms of the estimated healthcare revenues, my analysis addresses 71 percent of the total claim dollars in 2006.

⁵⁰ I received all the Ingenix modules; however, for reasons discussed later in the report, I examined only those listed in the table in detail.

Table 9: Summary of Ingenix 2006 Files

Description	CPT(CDT)	CPT(CDT)-by-Geozip ¹	Claims	Revenue ²
All files, all system codes	13,470	10,389,637	1,172,968,725	\$114,116,340,449
Anesthesia (all system codes)	3,739	231,352	1,240,522	\$1,022,656,581
HCPCS (HCPCS codes)	4,321	2,595,301	259,635,252	\$8,642,298,309
Dental (CDT codes)	514	274,053	155,039,899	\$15,452,709,148
<i>Empirical fees only³</i>	<i>391</i>	<i>170,742</i>	<i>154,885,321</i>	<i>\$15,386,945,805</i>
Medical (CPT codes 70000-99999)	2,976	2,598,653	692,745,148	\$64,507,518,225
Surgical (CPT codes 10000-69999)	5,394	4,840,137	54,497,933	\$22,681,243,431
Medical and Surgical	8,370	7,438,790	747,243,081	\$87,188,761,656
<i>Empirical fees only³</i>	<i>5,790</i>	<i>1,405,640</i>	<i>745,144,833</i>	<i>\$84,314,433,096</i>
<i>Empirical fees only³, selected system types⁴</i>	<i>5,713</i>	<i>1,323,720</i>	<i>713,012,637</i>	<i>\$80,774,839,146</i>

Notes:

1. Based on 899 Geozips.
2. Revenue = [mean value of fees]*[claims].
3. “Empirical fees” are those with record type of “30”
4. “Selected system types” include Medical, Surgical, Radiology total, and Pathology/Lab total.

62. In Table 9 above, I call the medical and surgical data based on nine or more charges “empirical fees.” These empirical fees account for 99.7% percent of the medical and surgical claim data. Plaintiffs have asserted that, “[a]ctual data is reported for just 10% of all CPT codes. Ingenix ‘derives’ data for the remaining 90% of CPT codes that have fewer than nine charges.”⁵¹ My review of the Ingenix Database shows that the majority of the pricing schedules for CPT codes in unique geozip records rely on derived data. The last column of Table 10 shows that over the various years of data, this proportion has been between 82 and 85 percent. The CPT-geozip combinations that rely on derived data, however, account for less than *one-half of one percent (0.005)* of the total claim count in the medical and surgical category, as shown in the sixth column of the table. In contrast, as noted above, the empirical data in the Ingenix Database account for over 99 percent of the number of claims in the Ingenix Database. As a result, I limited my comparative analysis of the benchmarks to Ingenix’s empirical fee data only.

Table 10: Summary of Medical and Surgical Empirical and Derived Values

Year	Claims						CPT-Geozip Records					
	Total		Empirical		Derived		Total		Empirical		Derived	
	Total No.	Empirical No.	% Total	No.	% Total	No.	Total No.	Empirical No.	% Total	No.	% Total	
2001	296,823,313	295,337,903	99.5%	1,485,410	0.5%	2,666,283	410,254	15.4%	2,256,029	84.6%		
2002	420,999,870	419,429,053	99.6%	1,570,817	0.4%	2,777,926	463,254	16.7%	2,314,672	83.3%		
2003	315,012,887	313,492,856	99.5%	1,520,031	0.5%	2,883,550	430,153	14.9%	2,453,397	85.1%		
2004	515,526,202	513,857,348	99.7%	1,668,854	0.3%	2,944,098	517,626	17.6%	2,426,472	82.4%		
2005	645,966,525	644,160,393	99.7%	1,806,132	0.3%	3,238,874	576,223	17.8%	2,662,651	82.2%		
2006	714,923,021	713,012,637	99.7%	1,910,384	0.3%	3,473,744	625,534	18.0%	2,848,210	82.0%		
2007	752,289,802	750,298,957	99.7%	1,990,845	0.3%	3,715,837	645,929	17.4%	3,069,908	82.6%		
2008	782,497,922	780,487,107	99.7%	2,010,815	0.3%	3,940,080	654,191	16.6%	3,285,889	83.4%		

63. Based on the information in the benchmark products, I developed a matched-pair methodology to compare information by upper percentile or average values, geographic

⁵¹ See Whittington Interrogatory at pp. 7-8. Accord Plaintiffs’ Collective Responses to Aetna’s Second Set of Interrogatories.

areas, and procedure description.⁵² Table 11 summarizes the comparison of values. PMIC and PFR did not include values for the 80th percentile.⁵³ Instead, their 75th percentile values were compared to the Ingenix 75th percentile value. NDAS did include an 80th percentile value and it was compared to the Ingenix 80th percentile value. MAG did not have percentile values for the fee distribution. MAG contained a fee range, which I define as “low” and “high” value ranges. The high value was not defined with respect to a percentile value, therefore I compared it separately to the Ingenix 80th and 90th percentile values. Medicare PSPS only contained data that could be compared to the Ingenix average values.

Table 11: Ingenix Values Matched by Benchmark

Benchmark	Average	75 th Percentile	80 th Percentile	90 th Percentile
MAG (high)			✓	✓*
Medicare PSPS	✓			
NDAS			✓	*
PFR		✓		
PMIC		✓		*
<u>Notes:</u>	* Used in the 2007 NYAG Report analysis.			

64. The restrictions I imposed on the matched-pair analysis reduces the number of CPTs (or CDTs), geozips, or combinations that I examine. Table 12 presents the implications of these restrictions. The more severe restrictions on complete datasets (i.e., not the subsets) reduced the number of comparisons (or coverage) to approximately 15 to 17 percent of the CPT-geozip “observations” in the Ingenix Database. The medical and surgical procedure comparisons included in my analysis, however, reflect between approximately 80 and 95 percent of the relevant claim count in the Ingenix Database and between approximately 83 and 92 percent of the relevant estimated revenue dollars for the 2006 data. The dental, or CDT, comparisons cover nearly all of the Ingenix claims and revenues as indicated by the percentages in the NDAS row of the table.

⁵² Specifically, Ingenix data are “matched” to the benchmark data for comparison by percentile (or mean value), CPT (or CDT) code, geographic area, and year. See Appendix B for details about the processing of the datasets to derive the matched pairs.

⁵³ As Plaintiffs acknowledge the 80th percentile value is a key value for determining the UCR. *See, e.g.*, Complaint at ¶ 346.

Table 12: Matched-Pair Coverage of Ingenix Observations

Benchmark	CPT(CDT)-by-Geographic Unit ^{1,2}	Claims	Revenue
MAG	17.9%	94.9%	92.2%
Medicare PSPS – all	15.4%	80.7%	83.3%
Medicare PSPS – subset³	7.1%	31.8%	30.4%
NDAS	61.7%	99.9%	99.6%
PFR	17.4%	94.9%	92.2%
PMIC – all	17.4%	94.9%	92.2%
PMIC – subset³	7.6%	33.7%	32.2%

Notes:

1. “Geographic units” indicate the geographic level of matched-pair comparison; i.e., geozip or 5-digit ZIP code. The geographic unit for all benchmarks except for MAG is at the geozip level; MAG is at the 5-digit ZIP code level.
2. The percentage of unique CPT-geographic units.
3. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips. For example, unless otherwise noted, “PMIC” refers to the complete database and “PMIC – subset” refers to the 30 CMS regions.

D. Empirical Analysis of Available Benchmarks

65. I investigate whether the Ingenix Database is biased downward systematically or across the board when compared to the available benchmarks. I use two major approaches in my analysis—frequency analysis of Ingenix values compared to the benchmark values, and a matched-pair analysis to examine summary measures of the comparisons controlling for geographic areas and medical services.

1. Frequency Analysis

66. As I understand Plaintiffs’ theory of impact, when compared to available information that is unaffected by the challenged conduct, Ingenix values, especially in the upper percentiles, are artificially low. A class-wide proof of common impact, according to this theory, would find that the actual Ingenix values are less than the values that would have prevailed but for the challenged conduct for all (or nearly all) members of the proposed classes. I therefore investigated how frequently Plaintiffs’ theory is true using the benchmark data.

67. My categories for the frequency analysis reflect the matching by geographic area. As discussed in Appendix B, to organize values geographically, some datasets used CMS regions, some geozips, and one uses a reported listing of city/areas. The different ways of defining the geographic area imply the need for additional processing to compare Ingenix to the benchmarks and different category definitions for the frequency analysis. PMIC and Medicare PSPS use CMS regions, which are often larger than Ingenix geozips and, therefore, often have one benchmark value for multiple Ingenix values. PFR and NDAS use geozips, but not collected into “records” as found in the Ingenix Database. PFR and NDAS therefore might have multiple benchmark values for one Ingenix value. Finally, MAG uses its city/area listing, which I processed to the five-digit zip codes that

best covered the geographic area of the name on the MAG list.⁵⁴ Aggregating the five-digit zip codes to the geozip level implies that there may be multiple MAG values for one Ingenix value. For any database with “multiple” values there is a Min and Max value. With this foundation about the comparisons, I define a set of mutually exclusive categories for the frequency comparisons as shown in Table 13.

Table 13: Geographically Based Categories for Frequency Comparisons

Benchmark	Geographic level of comparison	Categories
MAG	MAG region converted to 5-digit ZIP	1. Ingenix < Min MAG 2. Min MAG ≤ Ingenix ≤ Max MAG 3. Ingenix > Max MAG
Medicare PSPS	CMS region	1. Medicare PSPS > Max Ingenix 2. Min Ingenix ≤ Medicare PSPS ≤ Max Ingenix 3. Medicare PSPS < Min Ingenix
PMIC	CMS region	1. PMIC > Max Ingenix 2. Min Ingenix ≤ PMIC ≤ Max Ingenix 3. PMIC < Min Ingenix
Wasserman	Geozip, Geozip record	1. Ingenix < Min Wasserman 2. Min Wasserman ≤ Ingenix ≤ Max Wasserman 3. Ingenix > Max Wasserman

68. Based on the frequency categories above, I characterize “Plaintiffs’ theory” as the scenario where, for a given geographic area and CPT code, the Ingenix value (or the highest Ingenix value if I employ a geographic grouping for the purposes of comparison) is less than the benchmark value (or the lowest benchmark value if I employ a geographic grouping for the purposes of comparison). I characterize “Ambiguous” as the scenario where, for a given geographic area and CPT code, the Ingenix value is bounded by or bounds the benchmark value. I characterize “Contrary to Plaintiffs’ Theory” as the scenario where, for a given geographic area and CPT code, the Ingenix value (or the lowest Ingenix value if I employ a geographic grouping for the purposes of comparison) is greater than the benchmark value (or the highest benchmark value if I employ a geographic grouping for the purposes of comparison).

⁵⁴ MAG provides a tool that allows user to enter their 5-digit zip code to extract CPT values. My processing generally follows the methodology of MAG tool. I requested but could not directly obtain from MAG its complete mapping.

Table 14: Frequency Proportions for Each Benchmark (2006)

Benchmark	Plaintiffs' Theory	Ambiguous	Contrary to Plaintiffs' Theory
MAG – 80 th ¹	54%	5%	41%
MAG – 90 th ²	44%	5%	51%
Medicare PSPS – all ³	22%	42%	36%
Medicare PSPS – subset ^{3,4}	22%	44%	34%
NDAS ⁵	68%	2%	30%
PFR ⁶	56%	2%	42%
PMIC – all ⁶	26%	57%	17%
PMIC – subset ^{4,6}	24%	52%	24%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.

69. Regarding Plaintiffs’ theory of artificially low Ingenix values, the results shown in the second column of Table 14 above reveal that their theory is contradicted by more than half the comparisons as indicated by the proportions under 50 percent.⁵⁵ The results in the last column indicate that 17 to 51 percent of the comparisons are contrary to Plaintiffs’ theory. This proportion is an indication of the likelihood that the Ingenix value *exceeds* the maximum value for services by geographic area based on other available information. This evidence further suggests that many members of the proposed classes might have actually benefited from the use of the Ingenix Database to determine UCR rates. These members would not have an interest in using a different database to determine UCR in the world but for the challenged conduct.

2. Matched-Pair Metrics

70. To investigate class-wide proof of injury further, I compared the upper percentile Ingenix Database values with values from the commercial products and the distribution average with the average value in Medicare PSPS. My analysis compares “matched” values for a particular CPT in a particular geographic region. Appendix B contains details about how the geographic areas in one database were “mapped” to the Ingenix geozips. In some cases, a number of assumptions about city, county, or other socioeconomic boundaries were necessary to match to benchmarks that did not use geozips to segment geographic areas.

71. There is large variation in the magnitude of the values for CPT and CDT services. For example, at the 80th percentile, CPT codes⁵⁶ contain charges that vary from \$2 to

⁵⁵ I also examined a sensitivity analysis of the frequency analysis for PFR to investigate only the comparisons between PFR geozips and Ingenix geozip records. Limiting the analysis to this subset provides an estimate of the effects of pooling data over the geozip record. The frequency results were essentially the same for the restricted data.

⁵⁶ From the Ingenix 2006 database, CPT 86001 (ALLERGEN SPECIFIC IGG) contains the lowest charge amount, and CPT 47135 (TRANSPLANTATION OF LIVER) contains the highest charge amount.

\$43,603, and CDT codes⁵⁷ contain charges that vary from \$6 to \$11,890. A metric of comparison must normalize for scale. My comparisons are based on the percent difference in matched values—the same basic metric employed by the NYAG Report:

$$\text{Percent difference in values} = \frac{\text{Ingenix-Benchmark}}{\text{Benchmark}}$$

72. Each percent difference by CPT (or CDT) by geographic region yields an observation for the benchmark comparison.

- Negative percent differences indicate that the Ingenix value is less than the benchmark value and therefore could be consistent with Plaintiffs' theory of under reimbursement.
- Positive percent differences indicate that the Ingenix value exceeds the benchmark.

Importantly, a positive percent difference contradicts Plaintiffs' theory of common impact for CPT or CDT by geographic area combinations applicable to members of the proposed classes.

73. Summary metrics include simple averages of the percent difference observations and averages by claim or dollar spent:

$$\text{Claim weighted average} = \sum_{i=1}^n c_i x_i / \sum_{i=1}^n c_i$$

$$\text{Dollar weighted average} = \sum_{i=1}^n c_i r_i x_i / \sum_{i=1}^n c_i r_i$$

where n is the number of CPT-by-regions, x_i is the difference metric, c_i is the number of claims submitted for the CPT-by-region and r_i is the average (mean) Ingenix charge for each CPT-by-region.

In what follows, I generally report results for the simple averages of the matched pairs, with some exceptions. Appendix C contains the results for analyses not discussed in the body of this report. Overall, claim weighted and dollar weighed results are more contradictory of Plaintiffs' theory of a common downward bias than are the simple average results.

⁵⁷ From the Ingenix 2006 database, CDT D9215 (LOCAL ANESTHESIA) contains the lowest charge amount, and CDT D6078 (IMPLNT/ABUT DENTURE-COMPLT EDENT) contains the highest charge amount.

3. Average Percent Differences

74. The matched-pair analysis is designed to mimic the process of comparison that would occur for a given procedure in a given geographic area, using the same basic methodology as the NYAG Report. If the Ingenix values are artificially low, then I would expect to find persistent negative average percent differences when I compare Ingenix to the benchmarks. I also examine the variation of results in the comparison data to investigate the specific issue of common impact. If the Ingenix Database values are downwardly biased on an across-the-board basis for the purported classes, then I would expect to find all or nearly all results to show negative percent differences across benchmark comparisons on a consistent basis.

75. Comparison data were further pooled by AMA sections and subsections,⁵⁸ selected CPTs, and geographic regions to illustrate the heterogeneity of results across populations constructed from the comparisons.

a) National Results

76. Table 15 displays the results from the matched-pair comparisons in which all matches are weighted equally (“simple average”). The simple average results weigh all matched pairs equally. As a result, a high frequency CPT-geozip matched pair reflecting, for example, thousands of claims, is given the same weight in the average as a matched pair with a small number of claims. The second and fifth columns in the table indicate the total number of matched pairs generated by the data processing. The number of matched pairs is a reflection of the unique number of CPTs by geozips in the case when the benchmark uses geozips for the geographic area. It deviates most substantially in the case of the MAG comparisons which are made at the 5-digit zip code level to “cover” the geographic area of the reported MAG city/regions.⁵⁹

77. The results in the third and sixth columns of the table indicate that in those cases when the average percent differences are negative, they tend to be less than 5 percent, and in some cases, less than one percent. The largest positive values are found for the comparisons with MAG in 2005, with MAG in 2006 using the Ingenix 90th percentile value, and with Medicare PSPS in 2006. The PMIC and Medicare PSPS subsets, which reflect a perfect overlay with the Ingenix geozips, are positive in all cases.

78. Columns four and seven show the high proportion of the matched pairs that indicate a percent difference greater than or equal to zero. Consistent with the frequency analysis, this evidence reinforces the finding that many members of the proposed classes have actually benefited from the use of the Ingenix Database to determine UCR rates. These members would not have an interest in using one of the existing commercial or government databases to determine UCR in Plaintiffs’ “but-for” world.

⁵⁸ The AMA provides CPT codes categorized into six sections. Sections are further divided into subsections with subheadings based on anatomic, procedural, condition, or other descriptors. See American Medical Association. 2008. *Current Procedural Terminology CPT 2009 Professional Edition*. Chicago, IL: American Medical Association at p. xiv.

⁵⁹ Because MAG uses a range for fee values, two separate comparisons to MAG high are made using the 80th and 90th percentile values from Ingenix.

Table 15: Results of Simple Average of Matches

Benchmark	2005 ⁷			2006		
	No. of Matched Pairs	Average Percent Difference	Proportion of Matches ≥ 0	No. of Matched Pairs	Average Percent Difference	Proportion of Matches ≥ 0
MAG – 80 ^{th1}	59,594,766	9.38%	50%	61,196,195	-1.70%	37%
MAG – 90 ^{th2}	59,594,766	19.85%	60%	61,196,195	7.33%	48%
Medicare PSPS – all ³				1,273,476	12.86%	57%
Medicare PSPS – subset ^{3,4}				529,961	10.11%	55%
NDAS ⁵				169,082	-9.37%	31%
PFR ⁶				1,292,537	-0.83%	42%
PMIC – all ⁶	1,448,809	-3.09%	39%	1,467,942	-0.87%	41%
PMIC – subset ^{4,6}	543,678	2.41%	46%	563,362	4.88%	48%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.

79. Table 16 indicates the claim-weighted results of the analysis. For these results, matched pairs that have high claim amounts are weighted more heavily in the calculation of the average percent difference than those with low claim levels. The claim weighted average is an estimate of the percent difference between the Ingenix value and the benchmark per claim. Compared to the simple average results, there is a substantial reduction in the most negative average result. This result suggests that Ingenix values are more likely to exceed the benchmark for matched pairs with high claim counts. These results also contradict Plaintiffs’ theory of a common downward bias.

Table 16: Results of Claim-weighted Average of Matches

Benchmark	2005 ⁷	2006
MAG – 80 ^{th1}	4.44%	-5.99%
MAG – 90 ^{th2}	15.19%	3.79%
Medicare PSPS – all ³		7.94%
Medicare PSPS – subset ^{3,4}		7.78%
NDAS ⁵		-2.13%
PFR ⁶		-2.57%
PMIC – all ⁶	-0.78%	0.84%
PMIC – subset ^{4,6}	8.08%	10.77%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.

80. Table 17 shows the dollar-weighted percent difference averages. For these results, matched pairs that have high revenue values are weighted more heavily in the calculation of the average percent difference than those with low revenue values. The revenue weighted results are estimates for the percent difference per dollar spent. In all cases, the result is positive. Compared to the simple average, the Ingenix value is more likely to exceed the benchmark for service/geographic areas that have higher average charges. Importantly, none of the dollar weighted averages supports Plaintiffs' theory of a common downward bias.

Table 17: Results of Dollar-weighted Average of Matches

Benchmark	2005 ⁷	2006
MAG – 80 th ¹	10.97%	2.99%
MAG – 90 th ²	21.28%	12.60%
Medicare PSPS – all ³		14.78%
Medicare PSPS – subset ^{3,4}		14.95%
NDAS ⁵		1.67%
PFR ⁶		8.06%
PMIC – all ⁶	3.87%	5.64%
PMIC – subset ^{4,6}	12.43%	15.27%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. "Subset" is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.

81. My analysis of matched pairs for services by geographic areas on a national basis indicates that, when the Ingenix Database values are compared to the commercial and government benchmarks, the average percent differences are either (a) positive, which indicates that Ingenix values, on a national basis, tend to be higher than the benchmark, or (b) when the average percent differences are negative, they tend to be very small. These results do not support Plaintiffs' theory of a common downward bias.

82. In addition, there are substantial proportions of matched pairs, claims, and service revenues with Ingenix values that exceed the benchmark values. These data suggest that many members of the proposed classes have benefited from the use of Ingenix values as a basis for the UCR. If Aetna had used one of the existing alternative databases instead of the Ingenix Database to determine base case values for UCR charges, then these members of the proposed classes might have received lower ONET reimbursement.

b) Results by AMA Sections and Subsections

83. My analysis also indicates that, when the data are pooled into the AMA sections for the CPT codes, there is no evidence of a downward bias in the Ingenix data. Table 18 compares the average percent differences across benchmarks in each of the AMA

sections. The AMA sections are ordered from highest to lowest Ingenix claim count. The results show no clear pattern of low Ingenix Database values.

Table 18: Simple Average Percent Differences by AMA Section/Subsections

AMA Section/Subsection	Total Ingenix Claim Count	MAG	Medicare PSPS	PFR	PMIC
Medicine	260,471,368	-6%	11%	-3%	2%
Evaluation & Management	208,802,147	-1%	11%	4%	3%
Pathology, Lab	161,931,035	-11%	14%	-6%	-9%
Radiology	28,621,031	-7%	12%	-2%	-5%
Cardiovascular	18,865,330	6%	10%	-6%	-7%
Integumentary	16,232,069	6%	10%	-10%	4%
Musculoskeletal	5,349,731	10%	14%	9%	4%
Digestive System	3,838,609	-2%	12%	1%	3%
Urinary	1,487,111	17%	10%	19%	5%
Endocrine, Nervous	1,475,400	11%	16%	14%	8%
Female Genital	1,382,532	-3%	10%	-1%	1%
Respiratory	1,235,178	-6%	11%	-2%	1%
Eye	988,552	-7%	41%	11%	-1%
Maternity	934,024	-5%	23%	-2%	0%
Ear	870,644	11%	12%	11%	11%
Male Genital	413,428	14%	16%	10%	3%
Lymphatic	109,639	11%	24%	29%	1%
Mediastinum	4,809	18%	14%	15%	11%

Note:

* Percent differences that round to 0% are reported in black for all analyses.

c) Selected Procedural Results

- 84. An examination of the results for particular procedures in particular states demonstrates why information from existing benchmarks suggests an absence of classwide evidence of impact across all CPT codes and geographic areas. The examples below also illustrate the possibility of antagonistic interests among members of the proposed classes to select a benchmark compiled in the ordinary course of business. Table 19 to Table 21 display the claim-weighted average percent difference results from three illustrative examples.
- 85. The first two tables display results for procedures that Plaintiffs have referenced in the course of discovery.⁶⁰ Specific geographic areas were not generally mentioned by Plaintiffs except in the case of New Jersey. The other states in the tables were selected to illustrate the variation in the results.
- 86. The third example shows that even for the most frequently used CPT, results vary across and within benchmarks. Examples such as this reflect the basic difficulty that Plaintiffs face in developing a model for class-wide impact. My analysis of the existing benchmarks, which are all compiled and maintained apparently free of the challenged conduct, shows no support for a class-wide impact from the alleged flawed methodology used to process the Ingenix data, much less a finding of a common downward bias.

⁶⁰ See Cooper AET 00482-3 (citing CPT 36471); and Deposition Transcript of Brian Mullins (Feb. 22, 2010) at p. 69 (citing CPT 97001).

Table 19: Claim-weighted Percent Differences for CPT 36471 across Benchmarks in 2006

CPT = 36471¹					
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴	
Alaska	2%	-34%	4%	-8%	
Michigan	12%	-2%	3%	-31%	
Missouri	34%	-1%	24%	0%	
Virginia	-6%	2%	5%	-14%	
Washington	21%	-1%	20%	-4%	

Notes:

1. “Injection of sclerosing solution; multiple veins.”
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table 20: Claim-weighted Percent Differences for CPT 97001 across Benchmarks in 2006

CPT = 97001¹					
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴	
Alabama	-1%	10%	5%	0%	
Connecticut	-5%	1%	-3%	-7%	
Georgia	2%	-3%	-5%	-16%	
Nebraska	-4%	-13%	3%	0%	
New Jersey	-4%	3%	2%	-6%	

Notes:

1. “Physical therapy evaluation.”
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table 21: Claim-weighted Percent Differences for CPT 99213 across Benchmarks in 2006

CPT = 99213¹					
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴	
California	-2%	3%	4%	10%	
Florida	11%	2%	3%	-8%	
Mississippi	-1%	1%	0%	0%	
West Virginia	5%	0%	3%	-17%	

Notes:

1. “Office or other outpatient visit requiring an expanded problem-focused history.”
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

4. NY State Analysis

87. The NYAG Report provides an analysis of health care bills over the period 2004 through 2007 for five New York State counties, each containing a major city: (a) Albany; (b) Erie (Buffalo); (c) New York (Manhattan); (d) Monroe (Rochester); and (e) Onondaga (Syracuse).⁶¹ The analysis uses six CPT codes for doctors' office visits of varying complexity.⁶² The report describes the compilation of a "Model Database"⁶³ of charges to insurers for "certain ordinary doctors' office visits" in five subject counties. The report states that the NYAG compared the Model Database charges to the 80th percentile value from the 2007 Ingenix Database for each of the five counties. As noted, the NYAG Report defines the percent difference as I have done in my analysis.

88. Using the matched-pair methodology, the NYAG Report concludes:

Our analysis showed that insurers systematically under-reimburse New Yorkers for doctor's office visits. Statewide, consumers were underpaid by up to 28 percent[.] . . . For example, in New York County (Manhattan), underpayments were typically 10 to 20 percent[.]⁶⁴

89. The NYAG Report reported values from the Model Database for only two of the five subject counties.⁶⁵ The analysis apparently did not consider existing commercial and government databases as sources of benchmark values. I use the basic methodology of the NYAG Report to examine the results across benchmarks, not only for the five subject counties, but also for all counties in the state. The second column of Table 22 shows the only percent difference results reported in the NYAG Report. These results applied to New York and Erie counties. The other result columns show the comparable percent differences when the Ingenix Database is compared to the commercial benchmarks.

⁶¹ The NYAG Report uses counties to segment the geographic areas and CPT codes without modifiers for the product segmentation. The subject county boundaries are generally a more aggregate segmentation than the Ingenix geozip records.

⁶² The CPT Codes used in the NYAG Report include: (a) 99211; (b) 99212; (c) 99213; (d) 99214; (e) 99215; and (f) 99245.

⁶³ See NYAG Report at p. 20.

⁶⁴ See NYAG Report at p. 20.

⁶⁵ The full NYAG Report database has not been made available to me. I reserve the right to modify my analysis and opinions after a sufficient period of time to consider these data should they become available to me.

Table 22: Simple Average Percent Differences of Matches for Subject Counties and Subject CPT Codes Identified in the NYAG Report, 2007

County	NYAG Report*	MAG		PFR		PMIC	
		80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
Albany							
99211		9%	49%	2%	26%	24%	61%
99212		6%	19%	6%	10%	27%	25%
99213		3%	7%	8%	4%	24%	18%
99214		-7%	5%	5%	10%	15%	16%
99215		-9%	5%	5%	9%	14%	14%
99245		-4%	3%	22%	17%	20%	11%
Erie							
99211	-20%	-18%	0%	-20%	-18%	-3%	4%
99212	-22%	-16%	-6%	-20%	-16%	-5%	-4%
99213	-17%	-22%	-14%	-20%	-19%	-9%	-9%
99214	-19%	-22%	-13%	-15%	-11%	-7%	-6%
99215	-28%	-23%	-11%	-16%	-10%	-9%	-6%
99245	-26%	-27%	-21%	-14%	-13%	-16%	-18%
Monroe							
99211		0%	9%	1%	-10%	27%	18%
99212		0%	14%	-7%	3%	14%	21%
99213		-13%	0%	-6%	-6%	11%	10%
99214		-8%	7%	7%	9%	20%	19%
99215		-3%	13%	7%	15%	21%	24%
99245		3%	4%	28%	16%	30%	14%
New York							
99211	-20%	72%	72%	78%	45%	86%	59%
99212	-17%	41%	70%	45%	56%	48%	52%
99213	-14%	29%	61%	33%	55%	31%	51%
99214	-10%	18%	38%	35%	44%	27%	31%
99215	-1%	26%	27%	28%	31%	20%	18%
99245	0%	-1%	8%	19%	22%	1%	0%
Onondaga							
99211	-2%	16%	-8%	-7%	12%	18%	
99212	4%	12%	-1%	-1%	17%	11%	
99213	-6%	3%	-4%	-5%	9%	7%	
99214	-7%	4%	1%	4%	10%	9%	
99215	3%	7%	7%	5%	17%	9%	
99245	-11%	-7%	7%	1%	5%	-5%	
Notes:							
* See NYAG Report. The values depict upper bounds of the percent difference range presented in the NYAG Report.							

90. When the comparisons are extended beyond New York and Erie counties to include all counties in the state, the percent differences are either (a) positive, which indicates that Ingenix values, tend to be higher than the benchmark, or (b) when the average percent differences are negative, they tend to be very small, as shown in Table 23.⁶⁶ Pooling the data across the state also demonstrates that no benchmark is consistently higher than the Ingenix Database values.

⁶⁶ In addition, the 90th percentile comparisons for PMIC and PFR are in many cases more positive than the 75th percentile results. This is contrary to Plaintiffs' theory that the alleged flawed methodology downwardly biased the upper percentile values.

Table 23: Simple Average Percent Differences of Matches for Subject CPT Codes Identified in the NYAG Report across NY State, 2007

	MAG		PFR		PMIC	
	80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
99211	15%	31%	7%	5%	20%	23%
99212	7%	23%	-1%	7%	9%	12%
99213	-1%	13%	-1%	3%	5%	8%
99214	-6%	7%	2%	5%	3%	3%
99215	-6%	5%	-2%	3%	0%	0%
99245	-9%	-1%	4%	7%	-4%	-6%

91. Table 24 shows results for the subject counties and the state overall pooling the data across the subject CPTs. These results further suggest that based on percent differences, an allegation of downward bias cannot be supported across the state. At the very most, these results show that the Ingenix data for these CPT codes tend to be lower than the benchmarks for Erie County; but these results refute any conclusion that there is a systematic or statewide downward bias in the Ingenix data for these CPT codes. The absence of a common downward bias in the Ingenix Database values calls into question the reliability of the conclusions asserted in the NYAG Report.

Table 24: Simple Average Percent Differences of Matches Pooled across Subject CPT Codes Identified in the NYAG Report, 2007

	MAG		PFR		PMIC	
	80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
Albany	0%	15%	8%	13%	21%	24%
Erie	-21%	-11%	-18%	-15%	-8%	-6%
Monroe	-3%	8%	5%	5%	21%	18%
New York	31%	46%	40%	42%	36%	35%
Onondaga	-3%	6%	0%	-1%	12%	8%
Statewide	0%	13%	1%	5%	5%	7%

V. Conclusion

92. Plaintiffs have asserted that the Ingenix Database lacks a sufficient level of specificity and produces “False UCRs” for ONET reimbursement. My review indicates that commercial or government benchmarks have addressed the product segmentation and “genuine medical market” issues in various ways, but none approaches the level of segmentation advanced by Plaintiffs. Based on analysis of greater product or geographic segmentation than present in the Ingenix Database, my results indicate that comparison to data with greater segmentation does not support the conclusion that Ingenix values are systematically biased downward. On the contrary, greater segmentation through the use of charge modifiers or more narrowly defined geographic areas is likely to be a source of antagonistic interests among members of the proposed classes.

93. Moreover, even if the Ingenix database were the result of flawed methodology as Plaintiffs allege, there are no clear patterns of low values across services, AMA sections of services, or nationally. Overall, there is substantial variation in the comparison of

charge values across and within benchmarks. Across benchmarks, there is variation in the specific results, but no benchmark comparison indicates an across-the-board or pervasive downward bias of the upper percentile values or average charges in the Ingenix Database. As a result, substantial portions of members of the proposed classes likely would have conflicting interests in the selection of any one of these benchmarks—all of which are produced in the ordinary course of business—to measure impact.

94. My analysis of the existing benchmarks, which were available historically and are now readily available to Plaintiffs, demonstrates that no class-wide proof of systematic and pervasive downward bias is supported by the evidence. Under Plaintiffs' theory, a finding of no across-the-board downward bias in the Ingenix Database values is inconsistent with the alleged common impact of the challenged conduct for members of the purported classes.



Robin Cantor
April 6, 2010

APPENDIX A: ACQUISITION AND COMPILEDATION OF DATA SETS

Introduction

This appendix lists and details the acquisition and compilation of the data sets that are used in the benchmark analysis of the Cantor Expert Report. In most cases, the datasets are compiled from raw data that were obtained by Exponent from the following sources:

1. Ingenix¹
2. Practice Management Information Corporation (PMIC)²
3. Wasserman Medical Publishers
 - a. Physicians' Fee Reference (PFR)³
 - b. The National Dental Advisory Service Comprehensive Fee Report (NDAS)⁴
4. MAG Mutual Physicians' Fee & Coding Guide (MAG)⁵
5. Centers for Medicare & Medicaid Services Physician/Supplier Procedure Summary Master File (Medicare PSPS)⁶

Scanning Methodology for Databases Unavailable in an Electronic, Machine-readable Format

Some of the datasets used in analysis were available in electronic format; others were obtained in hard copy. The following section details Exponent's scanning methodology for data that were unavailable in an electronic format.

Certain benchmark databases (or portions thereof) were obtained in a physical, printed version. These benchmark databases include the following:

- MAG Mutual. 2004. *2005 Physicians Fee & Coding Guide*. Duluth, GA: MAG Mutual Healthcare Solutions, Inc. ("MAG 2005").
- MAG Mutual. 2006. *2007 Physicians Fee & Coding Guide*. Duluth, GA: MAG Mutual Healthcare Solutions, Inc. ("MAG 2007").
- Practice Management Information Corporation. 2005. *Medical Fees in the United States 2005*. Los Angeles, CA: Practice Management Information Corporation. ("PMIC

¹ See Prevailing Healthcare Charges System (PHCS), Ingenix.

² See, e.g., Practice Management Information Corporation. 2005. *Medical Fees in the United States 2005*. Los Angeles, CA: Practice Management Information Corporation.

³ See, e.g., Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2006. *Physicians' Fee Reference 2006*. Milwaukee, WI: Yale Wasserman, D.M.D. Medical Publishers, Ltd.

⁴ See, e.g., Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2007. *The Original National Dental Advisory Service 2007*. Milwaukee, WI: Yale Wasserman, D.M.D. Medical Publishers, Ltd.

⁵ See, e.g., MAG Mutual. 2007. *2008 Physicians Fee & Coding Guide*. Duluth, GA: MAG Mutual Healthcare Solutions, Inc.

⁶ See, e.g., Centers for Medicare & Medicaid Services. 2009. "Physician/Supplier Procedure Summary Master File," available at: http://www.cms.hhs.gov/NonIdentifiableDataFiles/06_PhysicianSupplierProcedureSummaryMasterFile.asp (last visited Mar. 10, 2010).

2005").

- Practice Management Information Corporation. 2007. *Medical Fees in the United States 2007*. Los Angeles, CA: Practice Management Information Corporation. ("PMIC 2007").
- Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2007. *The Original National Dental Advisory Service 2007*. Milwaukee, WI: Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2007. ("Wasserman 2007").

General Methodology for Data Entry

Exponent obtained physical versions of the above-referenced databases. Each database provided fee information for each CPT code in a generally consistent format on each page. The specific field headings that were recorded from each physical database are outlined below.

Exponent scanned the relevant portions of physical medium into an electronic-image format (the Portable Document Format ("PDF") of Adobe Systems Incorporated). Exponent then employed ABBYY FineReader 9.0 Professional Edition (*available at* www.abbyy.com), an optical character recognition ("OCR") software program, to translate the information contained in the PDF images into a machine-readable format (i.e., Microsoft Excel) (the "translated electronic databases").

For quality assurance, Exponent staff reviewed, in a line-by-line fashion, the information contained in the translated electronic database against the respective physical copy of that database.

In the event that the information contained in the translated electronic database, as obtained from the OCR process, did not match the information contained in the respective hard copy, the information contained in the respective hard copy governed. In these events, the Excel files were updated, and the information previously contained therein was superseded.

The PMIC 2005 and PMIC 2007 books provide fee information for each CPT code in a consistent format on each page. By way of illustration, each line entry on a page may or may not contain information under the following field headings:

- (a) CPT;
- (b) Short Description;
- (c) UCR 50th (i.e., the usual, customary, and reasonable fee at the 50th percentile);
- (d) UCR 75th (i.e., the usual, customary, and reasonable fee at the 75th percentile);
- (e) UCR 90th (i.e., the usual, customary, and reasonable fee at the 90th percentile);
- (f) MFS 2005 or MFS 2007, available in PMIC 2005 and PMIC 2007, respectively (i.e., the Medicare Fee Schedule for that year of publication); and

(g) MFS RVU (i.e., the Medicare Fee Schedule Relative Value Units for that year of publication).

Line-by-line review was limited to:

- (a) CPT;
- (b) UCR 50th (i.e., the usual, customary, and reasonable fee at the 50th percentile);
- (c) UCR 75th (i.e., the usual, customary, and reasonable fee at the 75th percentile);
- (d) UCR 90th (i.e., the usual, customary, and reasonable fee at the 90th percentile);

In the event that the information contained in the respective hard copy and/or PDF image file of that hard copy did not match the information contained in the PMIC Excel, as obtained from the OCR process, the information contained in the respective hard copy governed. In these events, the PMIC flat-file databases were updated, and the information previously contained therein was superseded.

Compilation of Datasets

SAS® version 9.2 is used for importing data files and programming the analysis. In order to compile the datasets, separate programs were created for each benchmark; each year is maintained separately within the program. In addition, once the datasets were compiled, successive programs were written to perform the analysis and determine the type and years of data available. As such, the data files imported into programs are renamed to start with the concurring program name to designate clearly which files are needed for each benchmark or analysis. Table A1 lists the programs written and executed.

Table A1 – SAS Programs Executed

Population.sas
Ingenix.sas
PMIC.sas
Wasserman.sas
MAG.sas
Analyses.sas
Coverage.sas
Medicare.sas
PSPS.sas
NY AG.sas

Ingenix Dataset

Program(s)

Population.sas
Ingenix.sas

Each record in the Ingenix dataset includes a field containing the number of occurrences (claims). Claims are adjusted by the population in their respective geographic area (geographic adjustment fact, or GAF), described below. Population.sas creates a dataset of the population based on the United States 2000 Census and the respective geographic areas (discussed in Appendix B). Ingenix.sas processes the medical, surgical, and dental Ingenix files, by compiling data, restricting types of claims for the analysis, expanding the geographic areas, and assigning a population weight to each geographic area.

Files

Exponent received medical, surgical, anesthesia, and HCPCS files for 2001-2008, and dental files for 2002-2007. Ingenix data from 2005 to 2007 were imported into SAS and each year maintained separately. For each imported data set, Ingenix's second annual update is used because it provides updates for the entire year. Files imported are listed in Table A2.

Table A2 – Imported Ingenix Files

Year	Type	File	Number of Records
2005	Medical	macdc.dat	1,388,307
2005	Surgical	sacdc.dat	2,131,046
2005	Anesthesia	astat.dat	104,008
2006	Medical	macdc.dat	1,513,444
2006	Surgical	sacdc.dat	2,267,047
2006	Anesthesia	astat.dat	108,739
2006	Dental	dstat.dat	127,554
2007	Medical	macdc.dat	1,608,373
2007	Surgical	sacdc.dat	2,434,297

Data Processing

The file format described in the document “PHCS Record Layout.pdf”⁷ was applied to the imported data. Each row provides fee information for a Current Procedural Terminology (“CPT”) or Current Dental Terminology (“CDT”) and geographic area. A dental benchmark is available only for 2006. Medical and surgical files are extracted for 2005, 2006, and 2007.

⁷ Ingenix, “PHCS Record Layout,” (2004).

For the analysis comparing Ingenix to other medical databases, the data used are restricted to “empirical” records where the number of occurrences (claims) in the database is 9 or higher. This is denoted in the dataset by requiring that the variable called “record type” is equal to 30.⁸ Additional restrictions applied to the data used include: 1) the system code is a CPT; and 2) the system type is 01: Surgical, 22: Medical, 33: Radiology total, or 55: Pathology/Lab. Professional fees are excluded from analysis.

A second Ingenix database was created using the dental files. The same file format was applied and the data used are restricted to records with at least 9 claims.

CPTs are classified according to the 18 American Medical Association (AMA) sections, shown in Table A3.

Table A3 – AMA Sections

System	CPT Code Range
Integumentary	10000-19999
Musculoskeletal	20000-29999
Respiratory	30000-32999
Cardiovascular	33000-37999
Lymphatic	38000-38999
Mediastinum	39000-39999
Digestive System	40000-49999
Urinary	50000-53999
Male Genital	54000-55999
Female Genital	56000-58999
Maternity	59000-59999
Endocrine, Nervous	60000-64999
Eye	65000-68999
Ear	69000-69999
Radiology	70000-79999
Pathology, Lab	80000-89999
Medicine	99000-99200; 99500-99999
Evaluation & Management	99200-99499

As noted above, Ingenix data files contain fee information for a CPT and a geographical area, defined as a single 3 digit zipcode (“geozip”) or collection of geozips (“geozip record”). For each geographic zip area, Ingenix provide the geozips covered and a geographic description. For example, the description of geographic zip area 100 notes, “NY-Manhattan (100-102).” Thus, the fee information for geozip 100 also applies to geozips 101 and 102. Exponent expanded the series in each year to create a unique set of CPTs and geozips. Using Manhattan as an example, separate entries are created in Ingenix for geozips 101 and 102, and the fee information for geozip 100 is applied to geozips 101 and 102. While the fee information applies to each geozip in the defined geographic zip area, the number of claims (occurrences) in the

⁸ Records with “derived” fee were excluded.

database is allocated by the relative population in the geozip (See Appendix B for further discussion).

In addition, Exponent restricted the comparison to the 50 states and Washington, D.C.; records for Puerto Rico and the Virgin Island are removed from both the medical/surgical and dental datasets.

Export

Depending upon the needs of matching to other benchmarks, two Ingenix data formats are created for some of the years. The first format is at the CPT-by-geozip level and the second format includes additional data references (Medicare carrier and localities). The datasets listed in Table A4 are stored for later use.

Table A4 – Datasets Created & Stored

Year	Dataset	Type	Includes Carriers & Localities
2005	ingenix05_census	Medical/Surgical	
	ingenix05_carrier	Medical/Surgical	Yes
2006	dingenix06_census	Dental	
	ingenix06_census	Medical/Surgical	
2007	ingenix06_carrier	Medical/Surgical	Yes
	ingenix07_census	Medical/Surgical	
	Ingenix07_carrier	Medical/Surgical	Yes

Summary

Exponent received medical, surgical, anesthesia, dental and HCPCS files from 2001-2008. Medical and surgical empirical fees of selected systems in 2005-2006 were used in analysis. Each dataset provides 50th, 60th, 70th, 75th, 80th, 85th, 90th, and 95th percentile values. Table A5, Table A6 and Table A7 present the summary of the different Ingenix files in 2005, 2006 and 2007 respectively, and also provide a summary of the datasets used for analysis. Once the geographic zip areas have been expanded, Ingenix contains a specific number of unique CPTs, geozips, and combinations thereof, which are available for matching to the other benchmarks.

Table A5 - Summary of Ingenix 2005 Files

Description	CPT	CPT-by-Geozip	Claims	Revenue
Ingenix All Files All system codes	13,127	10,378,334	1,012,770,131	\$97,148,868,806
Ingenix Anesthesia All system codes	3,771	226,885	877,838	\$709,034,547
Ingenix_HCPCS_-_HCPCS_codes	4,164	2,577,734	206,104,692	\$7,180,016,510
Ingenix_Dental_CDT_codes	533	459,318	118,483,454	\$11,053,669,582
Ing Dental empirical only	359	157,993	118,343,063	\$10,993,026,665
Ingenix_Medical_-_CPT_codes_70000-99999	2,855	2,498,854	628,752,503	\$56,625,736,888
Ingenix_Surgical_-_CPT_codes_10000-69999	5,308	4,763,523	47,539,092	\$19,658,048,547
Ingenix_Medical_Surgical_all	8,163	7,262,377	676,291,595	\$76,283,785,435
Ing_Med_Surg_empirical_only	5,607	1,364,172	674,300,730	\$73,650,069,787
Ing_Med_Surg_Emp_stype_01223355	5,520	1,280,979	644,160,393	\$70,404,001,074

¹Based on 901 geozips.

²Revenue = Mean value of fees x number of claims.

³Empirical fees are those with record type = 30.

⁴Selected system types = Medical, Surgical, Radiology total, Pathology/Lab total.

Table A6 - Summary of Ingenix 2006 Files

Description	CPT	CPT-by-Geozip	Claims	Revenue
Ingenix All Files All system codes	13,470	10,389,637	1,172,968,725	\$114,116,340,449
Ingenix_Anesthesia_All_system_codes	3,739	231,352	1,240,522	\$1,022,656,581
Ingenix_HCPCS_-_HCPCS_codes	4,321	2,595,301	259,635,252	\$8,642,298,309
Ingenix_Dental_CDT_codes	514	274,053	155,039,899	\$15,452,709,148
Ing_Dental_empirical_only	391	170,742	154,885,321	\$15,386,945,805
Ingenix_Medical_-_CPT_codes_70000-99999	2,976	2,598,653	692,745,148	\$64,507,518,225
Ingenix_Surgical_-_CPT_codes_10000-69999	5,394	4,840,137	54,497,933	\$22,681,243,431
Ingenix_Medical_Surgical_all	8,370	7,438,790	747,243,081	\$87,188,761,656
Ing_Med_Surg_empirical	5,790	1,405,640	745,144,833	\$84,314,433,096
Ing_Med_Surg_Emp_stype_01223355	5,713	1,323,720	713,012,637	\$80,774,839,146

¹Based on 899 geozips.

²Revenue = Mean value of fees x number of claims.

³Empirical fees are those with record type = 30.

⁴Selected system types = Medical, Surgical, Radiology total, Pathology/Lab total.

Table A7 - Summary of Ingenix 2007 Files

Description	CPT	CPT-by-Geozip	Claims	Revenue
Ingenix All Files All system codes	13,486	10,319,306	1,273,123,817	\$120,629,875,351
Ingenix_Anesthesia_All_system_codes	3,584	197,158	1,189,871	\$1,052,652,951
Ingenix_HCPCS_-_HCPCS_codes	4,299	2,494,146	323,983,286	\$9,887,246,549
Ingenix_Dental_CDT_codes	530	268,774	150,671,369	\$15,408,811,301
Ing_Dental_empirical_only	397	165,560	150,508,570	\$15,338,792,363
Ingenix_Medical_-_CPT_codes_70000-99999	2,954	2,592,139	731,734,695	\$69,303,094,219
Ingenix_Surgical_-_CPT_codes_10000-69999	5,440	4,884,026	54,026,277	\$22,946,043,462
Ingenix_Medical_Surgical_all	8,394	7,476,165	785,760,972	\$92,249,137,681
Ing_Med_Surg_empirical	5,860	1,373,240	783,553,655	\$89,141,636,489
Ing_Med_Surg_Emp_stype_01223355	5,764	1,284,589	750,298,957	\$85,342,686,814

Table A8 presents a list of the large volume and high revenue procedures in 2006 from the Ingenix data.

Table A8 - Large Volume and High Revenue Procedures in 2006

Highest Volume Procedures			Highest Revenue Procedures		
CPT	Description	No.	CPT	Description	Revenue
99213	OFFICE/OUTPATIENT VISIT EST	76,428,697	99213	OFFICE/OUTPATIENT VISIT EST	\$6,239,966,936
99214	OFFICE/OUTPATIENT VISIT EST	32,860,505	99214	OFFICE/OUTPATIENT VISIT EST	\$4,084,542,565
97110	THERAPEUTIC EXERCISES	27,879,951	97110	THERAPEUTIC EXERCISES	\$1,279,487,004
36415	ROUTINE VENIPUNCTURE	17,176,687	88305	TISSUE EXAM BY PATHOLOGIST	\$1,131,011,047
95165	ANTIGEN THERAPY SERVICES	16,272,861	99244	OFFICE CONSULTATION	\$1,082,956,829
97140	MANUAL THERAPY	15,434,961	90806	PSYTX OFF 45-50 MIN	\$1,038,872,374
95004	PERCUT ALLERGY SKIN TESTS	15,088,259	99203	OFFICE/OUTPATIENT VISIT NEW	\$981,475,040
99212	OFFICE/OUTPATIENT VISIT EST	14,629,116	59400	OBSTETRICAL CARE	\$937,032,119
98941	CHIROPRACTIC MANIPULATION	12,876,135	78465	HEART IMAGE (3D) MULTIPLE	\$904,897,590
80061	LIPID PANEL	11,115,516	99212	OFFICE/OUTPATIENT VISIT EST	\$887,940,497

Benchmarks

For the benchmarks against which Ingenix is compared (PMIC, NDAS, PFR, Medicare and MAG) the data are generally imported in two datasets. One set contains a listing of CPTs and fee information and the second set contains a list of areas and their associated geographic adjustment factors. To create a complete dataset, the datasets are joined such that every available CPT was linked to every available geographic area.

PMIC 2005

Program

PMIC.sas

PMIC.sas contains data compilation and processing code for PMIC. The complete dataset is then merged with the Ingenix dataset.

Data Acquisition

PMIC data from 2005 through 2007 were obtained from three different sources:

- 2005: Book purchased directly from PMIC at PMIConline.com,
- 2006: eBook (pdf version of hard copy of book) purchased directly from PMIC at PMIConline.com, and
- 2007: Book purchased from Amazon.com reseller.

Files

To use the PMIC 2005 data, the hard copy book was scanned into pdf files, which were then read into Excel as described above. Table A9 lists the files that were imported.

Table A9 – 2005 PMIC Files Imported

File	Description
PMIC_2005_Evaluation and Management.xls	List of CPTs and fee information
PMIC_2005_Medicine.xls	List of CPTs and fee information
PMIC_2005_Pathology and Laboratory.xls	List of CPTs and fee information
PMIC_2005_Radiology.xls	List of CPTs and fee information
PMIC_2005_Surgery.xls	List of CPTs and fee information
PMIC_2005_GAF.xls	List of GAFs and CMS regions
Population_ZPLCO105.xls	List of CMS regions and geozips

Data Processing

For PMIC, geographic regions are defined by the Centers for Medicare and Medicaid Services (CMS) regional assignments, which define regions by carrier and locality. The GAF files contain a list of CMS regions and assign geographic adjustment factors while the ZPLCO105 file list zip codes in each CMS region. The two files are combined to create a list of geozips, CMS regions and GAFs. The Evaluation and Management, Medicine, Pathology and Lab, Radiology, and Surgery files are combined to create a complete list of CPTs and fees.

In some instances, we identified geozips that were a perfect overlay with CMS regions. There were also instances in which geozips were identified in two or more CMS regions for which assumptions were made for how to allocate them, and therefore a different methodology was employed. Therefore, two PMIC datasets were produced for analysis: PMIC-subset and PMIC-all (discussed in Appendix B).

The two datasets are then cross joined, taking the product of the fee information file and the geographic referencing file. Thus, the complete PMIC 2005 dataset is generated for every possible CPT and geozip combination using the CPTs listed in PMIC 2005 and geozips listed in the CMS regional file (ZPLCO105).

Each CPT-by-geozip combination has an assigned CMS region and GAF and an adjustment is made to the fee based on the GAF. For example, the GAF for Alaska (carrier: 00831, locality: 01) is 1.05 in 2006. The 75th percentile for the data records of each CPT in that CMS region is created by multiplying the base values by 1.05.

Export

The comparison datasets of PMIC linked to Ingenix are ingenix_pmic05sub and ingenix_pmic05all.

Summary

Table A10 summarizes the number of CPTs, geozips and CPT-by-geozips combinations in the PMIC 2005 datasets.

Table A10 – 2005 PMIC Summary

CMS Regions	CPTs ¹	CPTs with -26 Modifier option	Geozips	CPT-by-Geozips
Subset	29	8132	880	399
All	92 ²	8132	880	917

¹Includes modified and unmodified CPTs.

²Includes Puerto Rico and Virgin Islands.

PMIC 2006

Program

PMIC.sas

PMIC.sas contains data compilation and processing code for PMIC. In the program, the fee information and geographic information are both compiled and processed. The complete dataset is then merged with the Ingenix dataset.

Files

To use the PMIC 2006 data, an electronic pdf file of PMIC 2006 was obtained and read into Excel; the fee information for all CPTs and the geographic referencing were separated into two files.

Table A11 lists the files that were imported.

Table A11 – 2006 PMIC Files Imported

File	Description
PMIC_2006_MedicalFees.xls	List of CPTs and fee information
PMIC_2006_GAF.xls	List of GAFs and CMS regions
Population_ZPLCO106.xls	List of CMS regions and geozips

Data Processing

The GAF and ZPLCO106 files are combined to create a list of geozips, CMS regions, and GAFs.

As with the PMIC 2005 dataset, due to several instances of geozips falling into two or more CMS regions, two PMIC datasets were produced for analysis: PMIC-subset and PMIC-all (discussed in Appendix B). The subset dataset contains geozips perfectly contained within CMS regions, whereas the all dataset includes all geozips, regardless of whether the geozip overlapped CMS regions.

The two datasets are then cross joined with the complete list of CPTs and fees (MedicalFees), thus generating a complete PMIC 2006 dataset for every possible CPT and geozip combination, using CPTs listed in PMIC 2006 and geozips listed in the CMS regional file (ZPLCO106).

The fees are multiplied by the respective geographic adjustment factor associated with the specified carrier and locality (as explained in the PMIC 2005 Data Processing description) to create service and area-specific records.

Export

The comparison datasets of PMIC linked to Ingenix are ingenix_pmic06sub and ingenix_pmic06all.

Summary

Table A12 summarizes the unique number of CPTs, geozips, and CPT-by-geozip combinations in the PMIC 2006 datasets.

Table A12 – 2006 PMIC Summary

CMS Regions	CPTs	CPTs with -26 Modifier option	Geozips	CPT by Geozips
PMIC-subset	30	8256	877	418
PMIC -all	91*	8256	877	917

*Includes Puerto Rico and Virgin Islands

Benchmark Resources available from Wasserman Medical Publishers

Data Acquisition

The Physicians' Fee Reference and the National Dental Advisory Service Comprehensive Fee Report were obtained from the following sources.

- 2006: PFR Book and data file purchased; NDAS book and data file purchased (all directly from Wasserman)
- 2007: PFR data file purchased (directly from Wasserman)

NDAS 2006

Program

Wasserman.sas

Wasserman.sas contains the data compilation and processing of both NDAS and PFR in 2006. For both benchmarks, the fee information and geographic referencing files are brought in, compiled and combined to create a complete data set for merging with Ingenix dental or medical/surgical databases.

Files

Exponent obtained a CD of the NDAS 2006 Pricing Program from which the National Fees for each CDT is exported (no geographic adjustment was applied). In the hard copy version, NDAS provides geographic adjustment factors for a list of geozips. This list was scanned into a pdf document and then read into Excel to acquire the geographic adjustment factors for each geozip. Table A13 lists the files that were imported.

Table A13 – 2006 NDAS Files Imported

File	Description
Wasserman_NDAS_2006_CDTFees.xls	List of CDTs and fee information
Wasserman_NDAS_2006_GAF.xls	List of GAFs and geozips

Data Processing

After importing the above files, a complete dataset for NDAS is produced by cross joining every CDT listed in NDAS to every geozip listed in the GAF file.

The fees are then multiplied by the respective geographic adjustment factor.

Export

The comparison dataset of Ingenix dental matched with NDAS is ingenix_ndas06.

Summary

Table A14 summarizes the unique number of CDTs, geozips, and CDT by geozip combinations in the NDAS 2006 dataset.

Table A14 – 2006 NDAS Summary

	CDTs	Geozips	CDT by Geozips
NDAS	561 (501 with fees)	911	511,071

PFR 2006

Program

Wasserman.sas

Files

The list of fee information at the national level for each CPT is exported from the PFR 2006 pricing program software (no geographic adjustment was applied to the list). The hard copy list of geographic adjustment factors and geozips was scanned and read into Excel. Table A15 lists the files that were imported.

Table A15 – 2006 PFR Files Imported

File	Description
Wasserman_PFR_2006_CPTFees.xls	List of CPTs and fee information
Wasserman_PFR_2006_GAF.xls	List of GAFs and geozips

Data Processing

A separate list of CPTs with modifiers (denoted as -26) is created and a binary variable added to the CPT and fee price data set indicating whether or not the CPTs have modifiers. After importing the above files, a complete dataset for PFR is produced by cross joining each CPT listed in PFR to every geozip listed in the GAF file.

The fees are then multiplied by the respective geographic adjustment factor.

Export

The comparison datasets of Ingenix medical/surgical matched with PFR is ingenix_pfr06.

Summary

Table A16 summarizes the unique number of CPTs, geozips, and CPT by geozips combinations in the PFR 2006 dataset.

Table A16 – 2006 PFR Summary

	CPTs	CPTs with -26 Modifier option	Geozips	CPT by Geozips
PFR	8256	953	912	7,529,472

MAG Mutual Physicians Fee & Coding Guide

Data Acquisition

Three years of data were obtained from the following sources.

- 2005: Fees on Disk purchased from MAG Mutual at MAGMutual.com
- 2006: Fees on Disk purchased from MAG Mutual at MAGMutual.com
- 2007: Book purchased from MAG Mutual at MAGMutual.com

MAG 2005

Program

MAG.sas

Instead of using CMS regions (as in PMIC) or geozips (as in the Wasserman datasets) to define the geographic area, MAG lists geographic adjustment factors for a single city, multiple cities, counties, or rural areas. Exponent defines each listing as a “collection.” Appendix B describes

the geographic referencing of the MAG data. MAG.sas imports several zip code databases to create a list of zip codes assigned to the various cities, counties or “collections” as designated by Exponent. Once the geographic assignment is complete, the program contains code for importing the fee information and creates a complete MAG dataset to be linked to Ingenix for both 2005 and 2006 data.

Files

The MAG2005 book is scanned into pdf files, which are later read into sections, separated by topic in Excel. The topics are Radiology, Medicine, Pathology and Laboratory, and Surgery. Table A17 lists the files that were imported.

Table A17 – 2005 MAG Files Imported

File	Description
ZIP-Codes-Database-deluxe-business.csv	List of zip codes and cities
ZIP-Codes-Database-multi-county.csv	List of zip codes and counties
Zip Code Block Conversion Files (50 files)	List of zip codes and census blocks
National.txt	List of states and counties
MAG_Geographic_Reference.xls	MAG Geographic Referencing Designation
Population_dc_dec_2000_sf1_u_data1.txt	U.S. Census Population
MAG_Mutual_2005_Radiology.xls	List of CPTs and fee information
MAG_Mutual_2005_Evaluation and Management.xls	List of CPTs and fee information
MAG_Mutual_2005_Medicine.xls	List of CPTs and fee information
MAG_Mutual_2005_Pathology and Laboratory.xls	List of CPTs and fee information
MAG_Mutual_2005_Surgery 1 of 5.xls	List of CPTs and fee information
MAG_Mutual_2005_Surgery 2 of 5.xls	List of CPTs and fee information
MAG_Mutual_2005_Surgery 3 of 5.xls	List of CPTs and fee information
MAG_Mutual_2005_Surgery 4 of 5.xls	List of CPTs and fee information
MAG_Mutual_2005_Surgery 5 of 5.xls	List of CPTs and fee information

Data Processing

After the geographic referencing is complete, the list of geozips and GAFs is cross joined with the fee information (Radiology, Evaluation and Management, Medicine, Pathology and Lab, and Surgery files). This creates a complete database for every possible geozip, GAF, and CPT combination from the geozips, GAFs and CPTs available from the zip code database and MAG 2005.

Instead of usual and customary fees, MAG provides a low fee and a high fee. The low and high fees are multiplied by the respective geographic adjustment factor.

Export

The comparison dataset of Ingenix medical/surgical matched with MAG is ingenix_mag05.

Summary

Table A18 summarizes the unique number of CPTs, zip codes, and CPT by zip code combinations in the MAG 2005 dataset.

Table A18 – 2005 MAG Files Imported

	CPTs	Zip Codes	CPT by Zip Codes
MAG	7957	41,132	327,287,324

MAG 2006

Program

MAG.sas

Files

Exponent acquired a CD of MAG Mutual Fees on Disk, which provides an Excel file of the CPTs and fees (Main Data File) and a word document of the geographic referencing (MAG Metropolitan Statistical Areas). The word document lists MAG geographically defined areas (earlier defined by Exponent as a “collection”), such as cities, counties or rural areas and the respective geographic adjustment factor MAG applied to that area. The geographic referencing document is read into Excel. A column of the classifications regarding the geographic zip code assignments is added (discussed in Appendix B).

Table A19 lists the files that were imported.

Table A19 – 2006 MAG Files Imported

File	Description
ZIP-Codes-Database-deluxe-business.csv	List of zip codes and cities
ZIP-Codes-Database-multi-county.csv	List of zip codes and counties
Zip Code Block Conversion Files (50 files)	List of zip codes and census blocks
National.txt	List of states and counties
MAG_Geographic_Reference.xls	MAG Collection designation
Population_dc_dec_2000_sf1_u_data1.txt	U.S. Census Population
MAG_2006_Main_Data_File_1.xls	List of CPTs and fee information

Data Processing

After the geographic referencing is complete, the list of geozips and GAFs is cross joined with the fee information (Main Data File) to create a complete database for every possible geozip, GAF, and CPT combination available from the zip code database and MAG 2006.

Instead of usual and customary fees, MAG provides a low fee and a high fee. The low and high fees are multiplied by the respective geographic adjustment factor.

Export

The comparison dataset of Ingenix medical/surgical matched with MAG is ingenix_mag06.

Summary

Table A20 summarizes the unique number of CPTs, zip codes, and CPT by zip code combinations in the MAG 2006 dataset.

Table A20 – 2006 MAG Summary

CPTs	Zip codes	CPT by Zip codes
MAG	8256	41,132

Medicare PSPS

Data Acquisition

Two years of the Physician/Supplier Procedure Summary Master File were acquired from the following sources.

- 2005: Physician/Supplier Procedure Summary Master File purchased from Centers from Medicare and Medicaid Services data distributor
- 2006: Physician/Supplier Procedure Summary Master File purchased from Centers from Medicare and Medicaid Services data distributor

Medicare PSPS 2006

Files

Program Medicare PSPS.sas

Physician/Supplier Procedure flat files from 2006 were purchased and read into SAS. Table A21 lists the files that were imported:

Table A21 – 2006 Medicare Files Imported

Files	
#00100	#59000
#10040A	#60000
#10040B	#65091
#20000A	#69000
#20000B	#70010A
#30000	#70010B
#33010	#80048
#38100	#90281
#39000	#99201
#40490	#ALPHAA
#50010	#ALPHAB
#54000	#ERRANT1
#56405	#ERRANT2

Data Processing

The Medicare data files listed above are imported according to the format specified in the PSPS Record Layout file (data dictionary). The files are then aggregated to create one complete dataset.

The Medicare flat files provide claims, charges and reimbursements for each CPT code in various CMS regions. The data are aggregated to calculate the total charges and reimbursement for each CPT and CMS region. Thus, the total number of claims and the sum of the submitted charges for each CPT, carrier and locality is calculated, along with the averages (sum of submitted charges/total number of claims).

Similar to PMIC, we identified geozips that were a perfect overlay with CMS regions. There were also instances in which geozips were identified in two or more CMS regions for which assumptions were made for how to allocate them, and therefore a different methodology was employed. Therefore, two Medicare PSPS datasets were produced for analysis: Medicare-subset and Medicare-all (discussed in Appendix B).

Summary

Table A22 summarizes the CMS regions and CPTs in the Medicare 2006 dataset.

Table A22 – 2006 Medicare PSPS Files Summary

CMS Regions	CPTs
542*	8396

*The data were restricted to numerical carriers, localities, or CPTs.

Additional Files: U.S. Census, CMS Regions, and Zip Code Files

Files

Table A23 lists the additional files outside of fee information or geographic referencing that are utilized in the data compilation of several benchmarks.

Table A23 – Additional Files Used in Analysis

	Files	Description
[1]	Population_dc_dec_2000_sf1_u_data1.txt	U.S. Census population for geozips
[2]	ZIP-Codes-Database-Standard.csv	List of zip codes
[3]	Population_ZPLCO105.xls	List of zip codes and CMS regions in 2005
[4]	Population_ZPLCO106.xls	List of zip codes and CMS regions in 2006
[5]	ZIP-Codes-Database-deluxe-business.csv	List of zip codes and cities
[6]	ZIP-Codes-Database-multi-county.csv	List of zip codes and counties
[7]	Zip Code Block Conversion Files (50 files)	List of zip codes and census blocks
[8]	National.txt	List of states and counties

Sources:

1: U.S. Census Bureau Website: http://factfinder.census.gov/servlet/DTGeoSearchByListServlet?ds_name=DEC_2000_SF1_U&_lang=en&_ts=288544597918.

2;5-8: See: <http://www.zip-codes.com/>

3-4: Via email request to Research Data Assistance Center, University of Minnesota, School of Public Health. See: <http://www.resdac.umn.edu/>

Data Processing

Population.sas, links U.S. Census population to an updated list of zip codes (ZIP Codes Database Standard), which is then linked to the zip codes in either ZPLCO105.xls or ZPLCO106.xls thereby creating a dataset of geozips, associated CMS regions, and respective populations. This population dataset is used to create the population weights in Ingenix (discussed in Appendix B).

The Zip Code Database files and national.txt assign zip codes to cities, counties, and CBSAs for use in MAG geographic referencing (Appendix B).

APPENDIX B: GEOGRAPHIC REFERENCING

Introduction

In order to compare Ingenix data to the various benchmarks, pairs are matched by CPT and geographic area. However, geographic referencing schemes vary by database. The different ways of defining the geographic area imply the need for additional processing to compare Ingenix to the benchmarks. The analysis requires a “mapping” from each benchmark to the geozip areas used in the Ingenix Database. The following sections explain the processes necessary for geographically referencing each benchmark. Once the geographic referencing is complete, each benchmark dataset is merged with the Ingenix dataset based on the geozip/zip code/CMS region.

Ingenix

As noted in Appendix A, the Ingenix data files contain fee information and the number of claims in the database for each CPT in a three-digit geozip. The series of geozips are split to create a geozip record or unique list of CPTs by geozips (also discussed in Appendix A).

Proportioning Claims

Since, in multiple cases, a single geozip in the Ingenix data is to be applied to multiple consecutive geozips, the number of claims needs to be apportioned to the individual geozips rather than to the first geozip in the data file. In order to perform this adjustment, Exponent uploaded the United States 2000 Census information to create population weights for each geozip (Population.sas, described in Appendix A). The claims are weighted by the population in the geozip relative to the population in the geozip collection. Using Manhattan as an example, the calculation of the number of claims for geozip 100 is:

$$\text{Geozip}_{100} \text{ claims} = [\text{Total Claims for geozip collection 100-102}] \times [(\text{Population in geozip}_{100}) / (\text{Population in geozips 100-102})]$$

PMIC

PMIC provides fee information for each CPT by combinations of carriers and localities, which are based on Centers for Medicare and Medicaid Services’ assignments, or “CMS regions.” “CMS regions” may comprise multiple states or may include only a single geozip. Generally, a CMS region is broader than, and in fact might segment geozips used in the Ingenix Database. The analysis addresses this issue by examining a subset of the data for which no additional matching assumptions are required as well as the full dataset, with mapping assumptions discussed in detail below.

Geographic Referencing

To take into account the fact that there are several cases where a geozip falls into two or more CMS regions, two analysis files for PMIC are created: PMIC-subset and PMIC-all (PMIC.sas). A CMS region matches perfectly with an Ingenix region if it completely contains and consists of a collection of geozips. This methodology yields 30 regions for comparison (29 states and Manhattan), hereafter called PMIC-subset. Otherwise, each CMS region is compared to the collection of geozips in that region, even if a geozip spans two or more CMS regions. This methodology, called PMIC-all, yields 89 regions for comparison (Puerto Rico and the Virgin Islands are not included). Table B1 lists the CMS regions in the subset and in the regions for which mapping assumptions are applied.

Table B1 – CMS Regions

Subset		Estimated Regional Matches		
Alabama	New Hampshire	Anaheim/Santa Ana, CA	Atlanta, GA	Rest of Maine
Alaska	New Mexico	Los Angeles, CA	Rest of Georgia	Detroit, MI
Arizona	Manhattan, NY	Marin/Napa/Solano, CA	Hawaii/Guam	Rest of Michigan
Arkansas	North Carolina	Oakland/Berkeley, CA	Idaho	Metropolitan KS City
Colorado	North Dakota	Rest of California 1	Chicago, IL	Metropolitan St. Louis
Delaware	Ohio	Rest of California 2	Suburban Chicago, IL	Rest of Missouri 1
Indiana	Oklahoma	San Francisco, CA	East St. Louis, IL	Rest of Missouri 2
Iowa	Rhode Island	San Mateo, CA	Rest of Illinois	Northern NJ
Kansas ¹	South Carolina	Santa Clara, CA	New Orleans, LA	Rest of New Jersey
Kentucky	South Dakota	Ventura, CA	Rest of Louisiana	NYC Suburbs/Long Is.
Minnesota	Tennessee	Connecticut	Metropolitan Boston	Poughkeepsie/North NYC Suburbs
Mississippi	Utah	DC and MD/VA Suburbs	Rest of MA	Queens, NY
Montana	Vermont	Fort Lauderdale, FL	Baltimore/Surrounding Counties MD	Rest of New York
Nebraska	West Virginia	Miami, FL	Rest of Maryland	Portland, OR
Nevada	Wisconsin	Rest of Florida	Southern Maine	Rest of Oregon

Notes:

1. PMIC lists two CMS regions in Kansas with the same GAF. CMS lists only one region for the entire state.

As an example of geozips falling into more than one CMS region, Figure B1 demonstrates how geozips 201, 206, and 207 span several CMS regions in the Washington, D.C./Maryland/Virginia area. In addition, geozip 207 appears in three CMS regions – carrier 12202 and locality 01 and carrier 12302, in both localities 01 and 99.

Figure B1 - Example of Overlapping Geozips

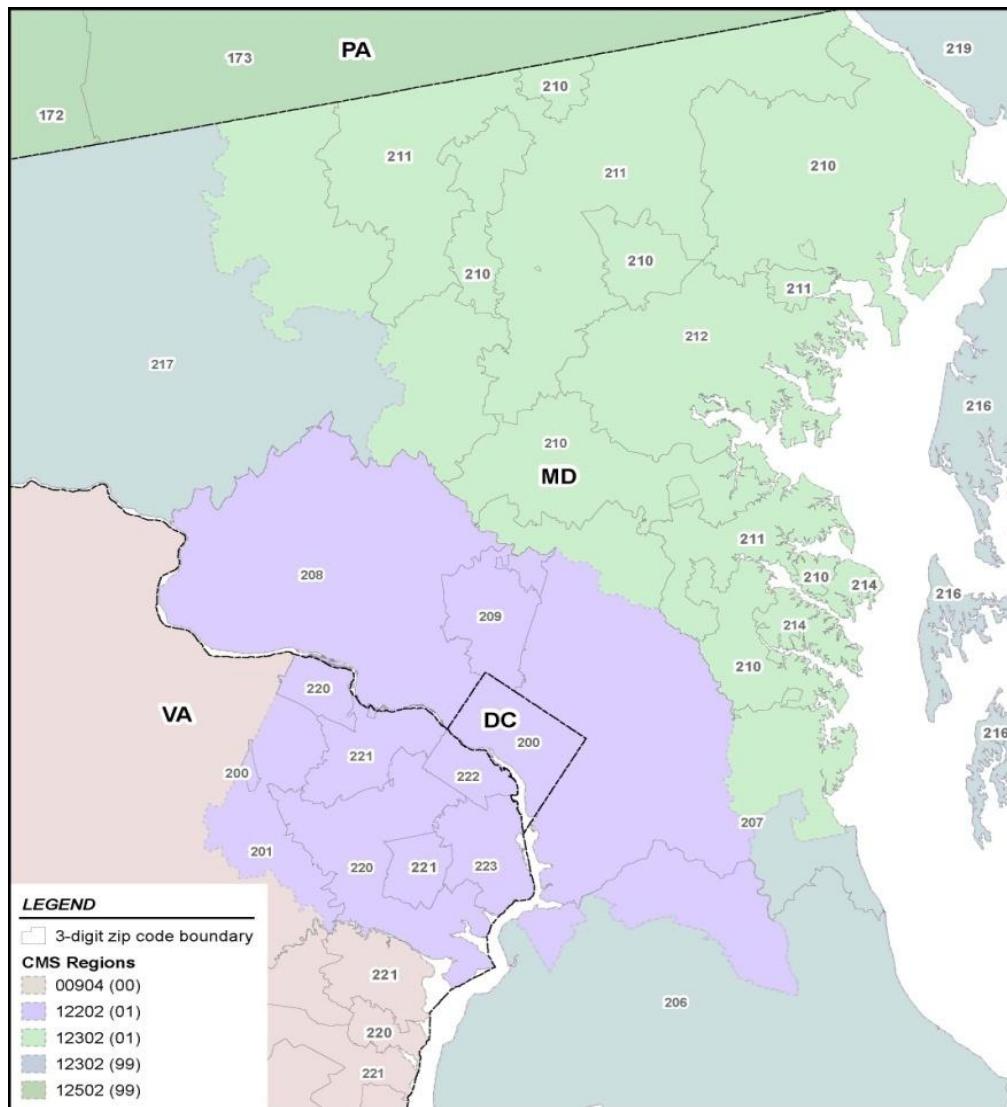
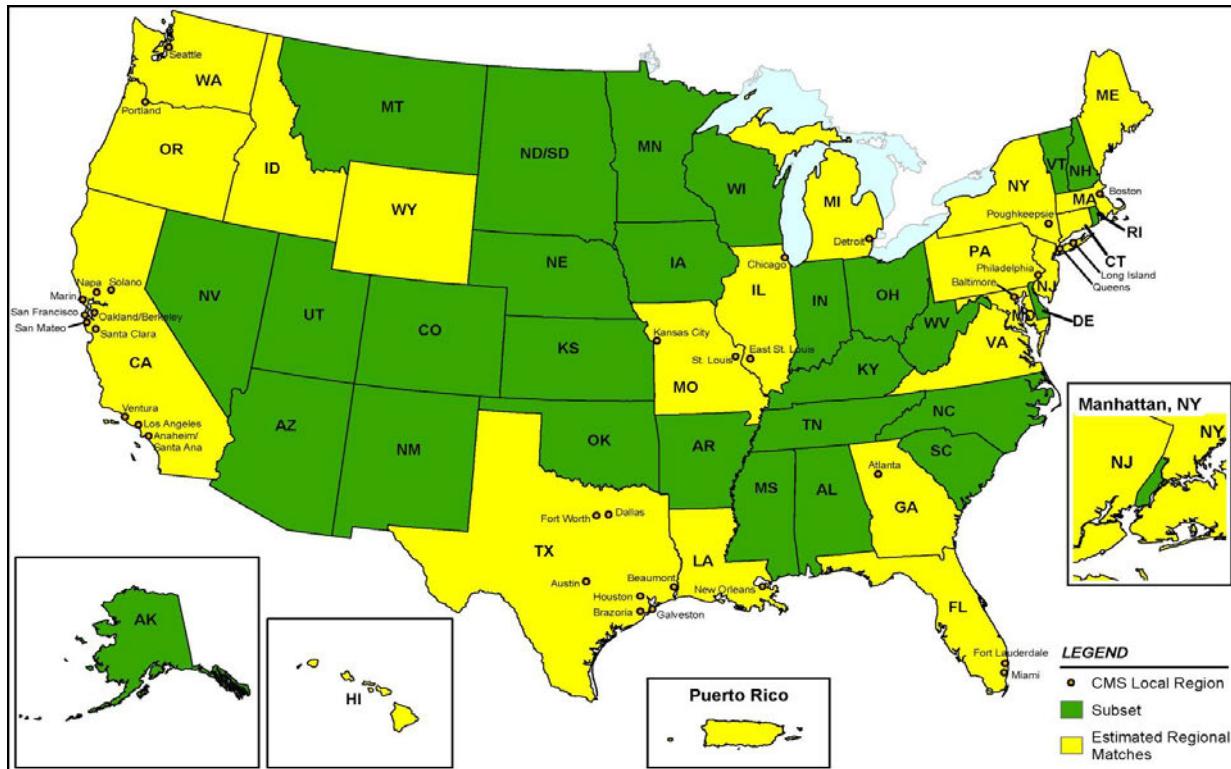


Figure B2 displays the CMS regions that are contained in the PMIC-subset and the CMS regions that fall into the PMIC-all category.

Figure B2 - Map of CMS Regions (Green) in the Subset and the Estimated Regional Matches (Yellow)



Matching with Ingenix

As mentioned previously, there are several instances where geozips falls into two or more CMS regions. In those cases, the number of claims is weighted by the proportion of the population in each CMS region. Hence, the Ingenix data are used in two formats (see Ingenix.sas, described in Appendix A). The first format is at the CPT-by-geozip level, where the number of claims are determined within a CMS region by its constituent geozips; the second format includes CMS regions by taking into account geozips crossing over multiple CMS regions. A CPT-by-geozip combination in this case may be listed multiple times if the geozip is located in multiple CMS regions and a 5-digit zip code mapping is used to apportion claims across CMS regions.

The PMIC-subset is matched to Ingenix based on CPT and geozip; the PMIC-all set is matched by CPT, CMS region, and geozip.

Coverage

Before matching, PMIC and Ingenix both contain a unique number of CPTs, geozips and CPT-by-geozips; the resulting comparison data set contains a set number of CPTs and geozips

contained in both Ingenix and PMIC. Table B2 and Table B3 provide the percent of coverage by CPT, geozip, CPT-by-geozips, total number of claims, and revenue of the comparison dataset relative to the datasets prepared for analysis.

Table B2 – 2005 Ingenix-PMIC Coverage

2005		CPT	Geozips	CPT-by-Geozips¹	Claims	Revenue
[1]	PMIC - all	8,132	917	7,456,127		
[2]	PMIC - subset	8,132	917	3,244,269		
[3]	Ingenix (medical and surgical)	8,163	901	7,262,377	676,291,595	\$76,283,785,435
[4]	PMIC - all -Ingenix comparison	5,501	899	1,274,192	643,668,950	\$70,312,078,310
[5]	PMIC - subset -Ingenix comparison	4,783	395	543,667	236,503,641	\$25,230,502,743
[4]/[3]	% Coverage of Ingenix (medical and surgical) – PMIC - all comparison	67.4%	99.8%	17.5%	95.2%	92.2%
[5]/[3]	% Coverage of Ingenix (medical and surgical) – PMIC - subset comparison	58.6%	43.8%	7.5%	35.0%	33.1%

¹The number of unique cpt-by-geozips.

Table B3 – 2006 Ingenix-PMIC Coverage

2006		CPT	Geozips	CPT-by-Geozips¹	Claims	Revenue
[1]	PMIC - all	8,256	917	7,570,752		
[2]	PMIC - subset	8,256	418	3,451,008		
[3]	Ingenix (all medical and surgical)	8,370	899	7,438,790	747,243,081	\$87,188,761,656
[4]	PMIC - all -Ingenix comparison	5,639	898	1,292,537	709,115,524	\$80,363,301,314
[5]	PMIC - subset -Ingenix comparison	4,928	413	563,362	251,561,929	\$28,036,126,197
[4]/[3]	% Coverage of Ingenix (medical and surgical) – PMIC - all comparison	67.4%	99.9%	17.4%	94.9%	92.2%
[5]/[3]	% Coverage of Ingenix (medical and surgical) – PMIC - subset comparison	58.9%	45.9%	7.6%	33.7%	32.2%

¹The number of unique cpt-by-geozips.

Medicare PSPS

Similar to PMIC, Medicare PSPS provides fee information for each CPT by combinations of carriers and localities, which are based on Centers for Medicare and Medicaid Services'

assignments, or “CMS regions.” “CMS regions” may comprise multiple states or may include only a single geozip.

A CMS region matches perfectly with an Ingenix region if it completely contains and consists of a collection of geozips. This methodology yields 30 regions for comparison (29 states and Manhattan), hereafter called “Subset.” Otherwise, each CMS region is compared to the collection of geozips in that region, even if a geozip spans two or more CMS regions. This methodology yields 89 regions for comparison (Puerto Rico and the Virgin Islands are not included). See Table B1 for CMS regions in the subset and in the regions for which mapping assumption are applied.

Geographic Referencing

Medicare PSPS data for each CPT is provided at the CMS region level. The data are used to calculate the average medical charge for each CPT-by-CMS region.

To take into account the fact that there are cases where a geozip falls in two or more CMS regions, two analysis files for Medicare PSPS are created: “subset” and “all” (Medicare PSPS.sas). In the first file, known as subset, CMS boundary regions match perfectly with a collection of mutually exclusive geozips. The second file, known as all, contains every geozip, even if it crosses 2 or more CMS regions.

Matching with Ingenix

The Medicare PSPS subset is matched to Ingenix based on CPT and geozip (first format of Ingenix); the Medicare PSPS all set is matched by CPT, CMS region, and geozip (second format of Ingenix).

Table B4 provides the percent of coverage by CPT, geozip, CPT-by-geozip, claim and revenue of the comparison dataset relative to the datasets prepared for analysis

Table B4 - 2006 Ingenix-Medicare Coverage

2005		CPT	Geozips	CPT-by-Geozips¹	Claims	Revenue
[1]	Medicare PSPS all regions	8,396	918	4,360,270		
[2]	Medicare subset	7,841	418	1,984,251		
[3]	Ingenix (medical and surgical)	8,370	899	7,438,790	747,243,081	\$87,188,761,656
[4]	Medicare all -Ingenix comparison	5,288	898	1,141,959	602,701,625	\$72,611,378,968
[5]	Medicare subset -Ingenix comparison	4,624	413	529,961	237,438,258	\$26,474,941,637
<hr/>						
[4]/[3]	% Coverage of Ingenix (medical and surgical) – Medicare all comparison	63.2%	99.9%	15.4%	80.7%	83.3%
[5]/[3]	% Coverage of Ingenix (medical and surgical) – Medicare subset comparison	55.2%	45.9%	7.1%	31.8%	30.4%

¹The number of unique cpt-by-geozips.

Wasserman

The Wasserman data (Physician's Fee Reference and National Dental Advisory Service) include fee information for each CPT and geozip.

Geographic Referencing

NDAS and PFR data are at the geozip level, thus, no assumptions are required to make perfect geographic matches.

Matching with Ingenix

NDAS and Ingenix dental are matched based on CDT and geozip; PFR and Ingenix (medical and surgical) are matched based on CPT and geozip (Wasserman.sas).

Coverage

NDAS, PFR, Ingenix Dental and Ingenix (medical/surgical) all contain a unique number of CDTs or CPTS, geozips and combination thereof. The resulting comparison data sets contain a set of CDTs or CPTs and geozips contained in both NDAS and Ingenix Dental or PFR and Ingenix (medical/surgical). Table B5 and Table B6 provide the percent of coverage by CPT, geozip, CPT-by-geozip, claim and revenue of the comparison dataset relative to the datasets prepared for analysis.

Table B5 - 2006 Ingenix-NDAS Coverage

2006	CDTs	Geozips	CDTs-by-Geozip¹	Claims	Revenue
NDAS	561	911	511,071		
Ingenix dental (all)	514	899	274,053	155,039,899	\$15,452,709,148
NDAS-Ingenix comparison	384	897	169,082	154,873,608	\$15,384,510,727
% Coverage of Ingenix	74.7%	99.8%	61.7%	99.9%	99.6%

*A total of 561 CDTs are listed, but only 501 have fees reported.

¹The number of unique cdt-by-geozips.

Table B6 - 2006 Ingenix-PFR Coverage

2006	CDTs	Geozips	CDTs-by-Geozip¹	Claims	Revenue
PFR	8,256	912	7,529,472		
Ingenix (all medical and surgical)	8,370	899	7,438,790	747,243,081	\$87,188,761,656
PFR-Ingenix comparison	5,639	898	1,292,537	709,115,524	\$80,363,301,314
% Coverage of Ingenix	67.4%	99.9%	17.4%	94.9%	92.2%

¹The number of unique cpt-by-geozips.

MAG

Data from MAG Mutual (Physicians' Fee and Coding Guide) provide a list of cities and counties that Exponent matched to zip codes.

Geographic Referencing

MAG Mutual not only provides a list of cities, counties, and states but also, at times, a collection of cities or a single city that cross state lines. For example, Memphis is listed three times – once each in Tennessee, Arkansas, and Missouri. After investigating the list, Exponent classified the collections into “Assigned Classifications” of cities, counties, and CBSAs (Core Based Statistical Areas). CBSAs are defined metropolitan statistical areas containing a population of similar economic and social identities;¹ CBSAs might consist of several counties. In order to map the collections to geozips, Exponent uses a commercially available zip code database² authorized by the United States Postal Service to match the cities, counties, and CBSAs to 5-digit zip codes. Since the true MAG assignment of zip codes to the collection names is unknown, Exponent developed a hierarchical set of rules to apply to the collections (MAG.sas), listed below:

¹ U.S. Census Bureau website. Metropolitan and Micropolitan Statistical Areas. <http://www.census.gov/population/www/metroareas/aboutmetro.html>

² www.zip-codes.com

- If the collection name is a single city in a single state, the zip codes associated with the city are applied to the collection name.
- If the collection name is a county, the zip codes associated with the county are applied to the collection name.
- If the collection name consists of several cities or a city listed in several states, Exponent checks whether the collection name matches the name of a CBSA.
 - If so, the associated counties are identified and zip codes assigned.
 - If the collection name does not match a CBSA, Exponent creates a convex set of zip codes to cover the area.
- Any area not designated to a MAG collection is assigned the “Rural” value of that state. In several instances, zip codes fall into two or more counties, which prevent assigning the geographic adjustment factor (GAF) at the 5-digit zip code level. The county with the highest proportion of the population for that zip code is the selected location of the zip code and its associated GAF.

Table B7 lists the MAG collection names, the classification, reasoning, and effective changes.

Table B7 - MAG Collection Names and Classifications by City, County or CBSA

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
ANCHORAGE	AK	Anchorage, AK	City		
RURAL	AK				
ANNISTON	AL	Anniston, AL	City		
BIRMINGHAM	AL	Birmingham, AL	City		
COLUMBUS	AL	Columbus GA-AL	CBSA	MAG lists Columbus in both AL and GA	
DOOTHAN	AL	Dothan, AL	City		
FLORENCE	AL	Florence, AL	City		
GADSDEN	AL	Gadsden, AL	City		
HUNTSVILLE	AL	Huntsville, AL	City		
MOBILE	AL	Mobile, AL	City		
MONTGOMERY	AL	Montgomery, AL	City		
TUSCALOOSA	AL	Tuscaloosa, AL	City		
RURAL	AL				
FAYETTEVILLE-SPRINGDALE	AR	Fayetteville-Springdale-Rogers AR-MO	CBSA		
FORT SMITH	AR	Fort Smith AR-OK	CBSA	MAG lists Fort Smith in AR and OK	
LITTLE ROCK-NORTH LITTLE ROCK	AR	Little Rock-North Little Rock-Conway AR	CBSA		
MEMPHIS	AR	Memphis TN-MS-AR	CBSA	MAG lists Memphis in AR and TN	
PINE BLUFF	AR	Pine Bluff, AR	City		
TEXARKANA	AR	Texarkana TX-Texarkana AR	CBSA	MAG lists Texarkana in AR and TX	
RURAL	AR				
PHOENIX	AZ	Phoenix, AZ	City		

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
TUCSON	AZ	Tucson, AZ	City		
RURAL	AZ				
ANAHEIM-SANTA ANA	CA	Santa Ana-Anaheim-Irvine, CA	CBSA Div		
BAKERSFIELD	CA	Bakersfield, CA	City		
CHICO	CA	Chico, CA	City		
FRESNO	CA	Fresno, CA	City		
LOS ANGELES-LONG BEACH	CA	Los Angeles-Long Beach-Glendale, CA	CBSA Div		
MERCED	CA	Merced, CA	City		
MODESTO	CA	Modesto, CA	City		
OAKLAND	CA	Oakland, CA	City		
OXNARD-VENTURA	CA	Oxnard-Thousand Oaks-Ventura CA	CBSA		
REDDING	CA	Redding, CA	City		
RIVERSIDE-SAN	CA	Riverside-San	CBSA		
BERNARDINO		Bernardino-Ontario CA			
SACRAMENTO	CA	Sacramento, CA	City		
SALINAS-SEASIDE-MONTEREY	CA	Salinas CA	CBSA		
SAN DIEGO	CA	San Diego, CA	City		
SAN FRANCISCO	CA	San Francisco, CA	City		
SAN JOSE	CA	San Jose, CA	City		
SANTA BARB-SANTA MARIA	CA	Santa Barbara-Santa Maria-Goleta CA	CBSA		
SANTA CRUZ	CA	Santa Cruz, CA	City		
SANTA ROSA-PETALUMA	CA	Santa Rosa-Petaluma CA	CBSA		
STOCKTON	CA	Stockton, CA	City		
VALLEJO-FAIRFIELD-NAPA	CA	Vallejo-Fairfield CA	CBSA		
VALLEJO-FAIRFIELD-NAPA	CA	Napa CA	CBSA		
VISALIA-TULARE-PORTERVILLE	CA	Visalia-Porterville CA	CBSA		
YUBA CITY	CA	Yuba City, CA	City		
RURAL	CA				
BOULDER-LONGMONT	CO	Boulder CO	CBSA		
COLORADO SPRINGS	CO	Colorado Springs, CO	City		
DENVER	CO	Denver, CO	City		
FORT COLLINS-LOVELAND	CO	Fort Collins-Loveland CO	CBSA		
GREELEY	CO	Greeley, CO	City		
PUEBLO	CO	Pueblo, CO	City		
RURAL	CO				
BRIDGEPORT-STAMFORD-NORWALK	CT	Bridgeport-Stamford-Norwalk CT	CBSA		
HARTFORD-MID-OWN-N BRIT	CT	Hartford-West Hartford-East Hartford CT	CBSA		
N HAVEN-W HAVEN-WBURY	CT	New Haven-Milford CT	CBSA		
NEW LONDON-NORWICH	CT	Norwich-New London CT	CBSA		
RURAL	CT				
WASHINGTON	DC	Washington-Arlington-Alexandria DC-VA-MD-WV	CBSA		
WILMINGTON	DE	Wilmington, DE-MD-NJ	CBSA Div		
RURAL	DE				
BRADENTON	FL	Bradenton, FL	City		
DAYTONA BEACH	FL	Daytona Beach, FL	City		
FORT LDALE-HLYWOOD-POM	FL	Fort Lauderdale-Pompano Beach-Deerfield Beach, FL	CBSA Div		
FORT MYERS-CAPE CORAL	FL	Cape Coral-Fort Myers FL	CBSA		
FORT PIERCE	FL	Fort Pierce, FL	City		

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
FORT WALTON BEACH	FL	Fort Walton Beach, FL	City		
GAINESVILLE	FL	Gainesville, FL	City		
JACKSONVILLE	FL	Jacksonville, FL	City		
LAKELAND-WINTER HAVEN	FL	Lakeland FL	CBSA		
MELBOURNE-TITUSVILLE	FL	Palm Bay-Melbourne-Titusville FL	CBSA		
MIAMI-HIALEAH	FL	Miami-Miami Beach-Kendall, FL	CBSA Div		
NAPLES	FL	Naples, FL	City		
OCALA	FL	Ocala, FL	City		
ORLANDO	FL	Orlando, FL	City		
PANAMA CITY	FL	Panama City, FL	City		
PENSACOLA	FL	Pensacola, FL	City		
SARASOTA	FL	Sarasota, FL	City		
TALLAHASSEE	FL	Tallahassee, FL	City		
TAMPA-ST.PBURG-CLRWATER	FL	Tampa-St. Petersburg-Clearwater FL	CBSA		
W P BEACH-BOCA RATON-DELR	FL	West Palm Beach-Boca Raton-Boynton Beach, FL	CBSA Div		
RURAL	FL				
ALBANY	GA	Albany, GA	City		
ATHENS	GA	Athens, GA	City		
ATLANTA	GA	Atlanta, GA	City		
AUGUSTA	GA	Augusta-Richmond County GA-SC	CBSA	MAG lists Augusta in GA and SC	
CHATTANOOGA	GA	Chattanooga TN-GA	CBSA	MAG lists Chattanooga in GA and TN	
COLUMBUS	GA	Columbus GA-AL	CBSA	MAG lists Columbus in AL and GA	
MACON-WARNER ROBBINS	GA	Macon GA	CBSA	Warner Robbins is in a different county than the Macon CBSA. List Warner Robins as a city.	
MACON-WARNER ROBBINS	GA	Warner Robins, GA	City		31028 – Centerville, GA
SAVANNAH	GA	Savannah, GA	City		
RURAL	GA				
HONOLULU	HI	Honolulu, HI	City		
RURAL	HI				
CEDAR RAPIDS	IA	Cedar Rapids, IA	City		
DES MOINES	IA	Des Moines, IA	City		
DUBUQUE	IA	Dubuque, IA	City		
IOWA CITY	IA	Iowa City, IA	City		
OMAHA	IA	Omaha-Council Bluffs NE-IA	CBSA	MAG lists Omaha in NE and IA	
SIOUX CITY	IA	Sioux City IA-NE-SD	CBSA	MAG lists Sioux City in NE and IA	
WATERLOO-CEDAR FALLS	IA	Waterloo-Cedar Falls IA	CBSA		
RURAL	IA				
BOISE CITY	ID	Boise, ID	City		
RURAL	ID				
AURORA-ELGIN	IL	Aurora, IL	City	*Aurora and Elgin are cities	60103 – Bartlett, IL; 60107 – Streamwood, IL; 60134 – Geneva, IL; 60174 - Saint Charles, IL; 60175 - Saint Charles, IL; 60177 - South Elgin, IL; 60184 – Wayne, IL; 60185 - West Chicago, IL; 60510 – Batavia, IL; 60539 – Mooseheart, IL; 60542 -

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
AURORA-ELGIN	IL	Elgin, IL	City		North Aurora, IL; 60555 -
BLOOMINGTON-NORMAL	IL	Bloomington-Normal IL	CBSA		Warrenville, IL
CHAMPAIGN-URBANA-RANTO	IL	Champaign-Urbana IL	CBSA		
CHICAGO	IL	Chicago, IL	City		
DAVENPORT-ROCK IS-MOLINE	IL	Davenport-Moline-Rock Island IA-IL	CBSA		
DECATUR	IL	Decatur, IL	City		
JOLIET	IL	Joliet, IL	City		
KANKAKEE	IL	Kankakee, IL	City		
LAKE COUNTY	IL	Lake	County		
PEORIA	IL	Peoria, IL	City		
ROCKFORD	IL	Rockford, IL	City		
SPRINGFIELD	IL	Springfield, IL	City		
ST. LOUIS	IL	St. Louis MO-IL	CBSA		
RURAL	IL				
ANDERSON	IN	Anderson, IN	City		
BLOOMINGTON	IN	Bloomington, IN	City		
CINCINNATI	IN	Cincinnati-Middletown OH-KY-IN	CBSA	MAG lists Cincinnati in IN and OH	
ELKHART-GOSHEN	IN	Elkhart-Goshen IN	CBSA		
EVANSVILLE	IN	Evansville IN-KY	CBSA	MAG lists Evansville in IN and KY	
FORT WAYNE	IN	Fort Wayne, IN	City		
GARY-HAMMOND	IN	Gary, IN	CBSA Div		
INDIANAPOLIS	IN	Indianapolis, IN	City		
KOKOMO	IN	Kokomo, IN	City		
LAFAYETTE	IN	Lafayette, IN	City		
LOUISVILLE	IN	Louisville/Jefferson County KY-IN	CBSA	MAG lists Louisville in IN and KY	
MUNCIE	IN	Muncie, IN	City		
SOUTH BEND-MISHAWAKA	IN	South Bend-Mishawaka IN-MI	CBSA		
TERRE HAUTE	IN	Terre Haute, IN	City		
RURAL	IN				
KANSAS CITY	KS	Kansas City MO-KS	CBSA		
LAWRENCE	KS	Lawrence, KS	City		
TOPEKA	KS	Topeka, KS	City		
WICHITA	KS	Wichita, KS	City		
RURAL	KS				
CINCINNATI	KY	Cincinnati-Middletown OH-KY-IN	CBSA		
CLARKSVILLE-HOPKINSVILLE	KY	Clarksville TN-KY	CBSA		
HUNTINGTON-ASHLAND	KY	Huntington-Ashland WV-KY-OH	CBSA		
LEXINGTON-FAYETTE	KY	Lexington-Fayette KY	CBSA		
LOUISVILLE	KY	Louisville/Jefferson County KY-IN	CBSA		
OWENSBORO	KY	Owensboro, KY	City		
RURAL	KY				
ALEXANDRIA	LA	Alexandria, LA	City		
BATON ROUGE	LA	Baton Rouge, LA	City		
HOUMA-THIBODAUX	LA	Houma-Bayou Cane-Thibodaux LA	CBSA		
LAFAYETTE	LA	Lafayette, LA	City		
LAKE CHARLES	LA	Lake Charles, LA	City		
MONROE	LA	Monroe, LA	City		
NEW ORLEANS	LA	New Orleans, LA	City		
SHREVEPORT	LA	Shreveport, LA	City		
RURAL	LA				
BOSTON-LOWELL-BRKTON	MA	Boston-Cambridge-	CBSA		

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
N BEDFORD-F RIVER-ATTLEB	MA	Quincy MA-NH Providence-New Bedford-Fall River RI-MA	CBSA		
PITTSFIELD	MA	Pittsfield, MA	City		
SPRINGFIELD	MA	Springfield, MA	City		
WORCESTER-FBURG-LEOMIN	MA	Worcester MA	CBSA		
RURAL	MA				
BALTIMORE	MD	Baltimore, MD	City		
CUMBERLAND	MD	Cumberland MD-WV	CBSA	MAG lists Cumberland in MD and WV	
HAGERSTOWN	MD	Hagerstown, MD	City		
WASHINGTON	MD	Washington-Arlington-Alexandria DC-VA-MD-WV	CBSA	MAG lists Washington in MD and DC	
WILMINGTON	MD	Wilmington, DE-MD-NJ	CBSA Div	MAG lists Wilmington in MD and DE	
RURAL	MD				
BANGOR	ME	Bangor, ME	City		
LEWISTON-AUBURN	ME	Lewiston-Auburn ME	CBSA		
PORTLAND	ME	Portland, ME	City		
RURAL	ME				
ANN ARBOR	MI	Ann Arbor, MI	City		
BATTLE CREEK	MI	Battle Creek, MI	City		
BENTON HARBOR	MI	Niles, MI	City		
DETROIT	MI	Detroit, MI	City		
FLINT	MI	Flint, MI	City		
JACKSON	MI	Jackson, MI	City		
KALAMAZOO	MI	Kalamazoo, MI	City		
LANSING-EAST LANSING	MI	Lansing-East Lansing MI	CBSA		
MUSKEGON	MI	Muskegon, MI	City		
SAGINAW-BAY CITY-	MI	Saginaw-Saginaw Township North MI	CBSA		
MIDLAND	MI				
SAGINAW-BAY CITY-	MI	Bay City MI	CBSA		
MIDLAND	MI				
SAGINAW-BAY CITY-	MI	Midland MI	CBSA		
MIDLAND	MI				
RURAL	MI				
DULUTH	MN	Duluth MN-WI	CBSA		
FARGO-MOORHEAD	MN	Fargo ND-MN	CBSA		
MINNEAPOLIS-ST. PAUL	MN	Minneapolis-St. Paul-Bloomington MN-WI	CBSA		
ROCHESTER	MN	Rochester, MN	City		
ST. CLOUD	MN	Saint Cloud, MN	City		
RURAL	MN				
COLUMBIA	MO	Columbia, MO	City		
JOPLIN	MO	Joplin, MO	City		
KANSAS CITY	MO	Kansas City MO-KS	CBSA		
SPRINGFIELD	MO	Springfield, MO	City		
ST JOSEPH	MO	Saint Joseph, MO	City		
ST. LOUIS	MO	St. Louis MO-IL	CBSA		
RURAL	MO				
BILOXI-GULFPORT	MS	Gulfport-Biloxi MS	CBSA		
JACKSON	MS	Jackson, MS	City		
MEMPHIS	MS	Memphis TN-MS-AR	CBSA	MAG lists Memphis in multiple states	
PASCAGOULA	MS	Pascagoula, MS	City		
RURAL	MS				
BILLINGS	MT	Billings, MT	City		
GREAT FALLS	MT	Great Falls, MT	City		
RURAL	MT				

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
ASHEVILLE	NC	Asheville, NC	City		
BURLINGTON	NC	Burlington, NC	City		
CHARLOTTE-GASTONIA-R	NC	Charlotte-Gastonia-	CBSA		
HILL		Concord NC-SC			
GREENSBORO-WINSALEM-HIGH	NC	Greensboro-High Point NC	CBSA		
GREENSBORO-WINSALEM-HIGH	NC	Winston-Salem NC	CBSA		
HICKORY	NC	Hickory, NC	City		
JACKSONVILLE	NC	Jacksonville, NC	City		
RALEIGH-DURHAM	NC	Raleigh-Cary NC	CBSA		
RALEIGH-DURHAM	NC	Durham NC	CBSA		
WILMINGTON	NC	Wilmington, NC	City		
RURAL	NC				
BISMARCK	ND	Bismarck, ND	City		
FARGO-MOORHEAD	ND	Fargo ND-MN	CBSA		
GRAND FORKS	ND	Grand Forks, ND	City		
RURAL	ND				
LINCOLN	NE	Lincoln, NE	City		
OMAHA	NE	Omaha-Council Bluffs NE-IA	CBSA	MAG lists city in two states	
SIOUX CITY	NE	Sioux City IA-NE-SD	CBSA	MAG lists city in two states	
RURAL	NE				
MANCHESTER-NASHUA	NH	Manchester-Nashua NH	CBSA		
PSMOUTH-DOVER-ROCHEST	NH	Rockingham County-Strafford County, NH	CBSA Div		
RURAL	NH				
ATLANTIC CITY	NJ	Atlantic City, NJ	City		
BERGEN-PASSAIC	NJ	New York-White Plains-Wayne, NY-NJ	CBSA Div		
JERSEY CITY	NJ	Jersey City, NJ	City		
MDLSEX-SRSET-HUNTERDON	NJ	Middlesex	County	In reference to counties, not cities	
MDLSEX-SRSET-HUNTERDON	NJ	Somerset	County	Monmount is Monmouth	
MDLSEX-SRSET-HUNTERDON	NJ	Hunterdon	County		
MONMOUNT-OCEAN	NJ	Monmouth	County		
MONMOUNT-OCEAN	NJ	Ocean	County		
NEWARK	NJ	Newark, NJ	City		
PHILADELPHIA	NJ	Philadelphia, PA	CBSA Div		
PHILADELPHIA	NJ	Camden, NJ	CBSA Div		
TRENTON	NJ	Trenton, NJ	City		
VLAND-MILLVILLE-BRIDGETON	NJ	Vineland-Millville-Bridgeton NJ	CBSA		
WILMINGTON	NJ	Wilmington, DE-MD-NJ	CBSA Div		
RURAL	NJ				
ALBUQUERQUE	NM	Albuquerque, NM	City		
LAS CRUCES	NM	Las Cruces, NM	City		
SANTA FE	NM	Santa Fe, NM	City		
RURAL	NM				
LAS VEGAS	NV	Las Vegas, NV	City		
RENO	NV	Reno, NV	City		
RURAL	NV				
ALBANY-SCHENECTADY-TROY	NY	Albany-Schenectady-Troy NY	CBSA		
BINGHAMTON	NY	Binghamton, NY	City		
BUFFALO	NY	Buffalo, NY	City		
ELMIRA	NY	Elmira, NY	City		
GLENS FALLS	NY	Glens Falls, NY	City		
NASSAU-SUFFOLK	NY	Nassau-Suffolk, NY	CBSA Div		
NEW YORK	NY	New York	County		
NEW YORK	NY	Bronx	County		

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
NEW YORK	NY	Queens	County		
NEW YORK	NY	Richmond	County		
NEW YORK	NY	Kings	County		
NIAGARA FALLS	NY	Niagara Falls, NY	City		
ORANGE COUNTY	NY	Orange	County		
POUGHKEEPSIE	NY	Poughkeepsie, NY	City		
ROCHESTER	NY	Rochester, NY	City		
SYRACUSE	NY	Syracuse, NY	City		
UTICA-ROME	NY	Utica-Rome NY	CBSA		
RURAL	NY				
AKRON	OH	Akron, OH	City		
CANTON	OH	Canton, OH	City		
CINCINNATI	OH	Cincinnati-Middletown OH-KY-IN	CBSA	MAG lists Cincinnati in 3 states	
CLEVELAND	OH	Cleveland, OH	City		
COLUMBUS	OH	Columbus, OH	City		
DAYTON-SPRINGFIELD	OH	Dayton OH	CBSA		
HAMILTON-MIDDLETOWN	OH	Hamilton, OH	City	*Hamilton and Middletown are cities.	45067 – Trenton, OH
HAMILTON-MIDDLETOWN	OH	Middletown, OH	City		
HUNTINGTON-ASHLAND	OH	Huntington-Ashland WV-KY-OH	CBSA		
LIMA	OH	Lima, OH	City		
LORAIN-ELYRIA	OH	Lorain, OH	City	*Lorain and Elyria are cities No gap between cities.	
LORAIN-ELYRIA	OH	Elyria, OH	City		
MANSFIELD	OH	Mansfield, OH	City		
PARKERSBURG-MARIETTA	OH	Parkersburg-Marietta-Vienna WV-OH	CBSA		
STEUBENVILLE-WEIRTON	OH	Weirton-Steubenville WV-OH	CBSA		
TOLEDO	OH	Toledo, OH	City		
WHEELING	OH	Wheeling WV-OH	CBSA	MAG lists Wheeling in OH and WV	
YOUNGSTOWN-WARREN	OH	Youngstown-Warren-Boardman OH-PA	CBSA		
RURAL	OH				
ENID	OK	Enid, OK	City		
FORT SMITH	OK	Fort Smith AR-OK	CBSA	MAG lists Fort Smith in OK and AR	
LAWTON	OK	Lawton, OK	City		
OKLAHOMA CITY	OK	Oklahoma City, OK	City		
TULSA	OK	Tulsa, OK	City		
RURAL	OK				
EUGENE-SPRINGFIELD	OR	Eugene-Springfield OR	CBSA		
MEDFORD	OR	Medford, OR	City		
PORTLAND	OR	Portland, OR	City		
SALEM	OR	Salem, OR	City		
RURAL	OR				
ALLENTOWN-BETHLEHEM	PA	Allentown-Bethlehem-Easton PA-NJ	CBSA		
ALTOONA	PA	Altoona, PA	City		
BEAVER	PA	Beaver	County		
ERIE	PA	Erie, PA	City		
HRSBURG-LEBANON-CARLISE	PA	Harrisburg-Carlisle PA	CBSA	Lebanon is its own CBSA	
HRSBURG-LEBANON-CARLISE	PA	Lebanon PA	CBSA		
JOHNSTOWN	PA	Johnstown, PA	City		
LANCASTER	PA	Lancaster, PA	City		

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
PHILADELPHIA	PA	Philadelphia, PA	CBSA Div		
PHILADELPHIA	PA	Camden, NJ	CBSA Div		
PITTSBURGH	PA	Pittsburgh, PA	City		
READING	PA	Reading, PA	City		
SCRANTON-WILKES BARRE	PA	Scranton--Wilkes-Barre PA	CBSA		
SHARON	PA	Sharon, PA	City		
STATE COLLEGE	PA	State College, PA	City		
WILLIAMSPORT	PA	Williamsport, PA	City		
YORK	PA	York, PA	City		
RURAL	PA				
PROV-PTUCKET-WNSOCK	RI	Providence-New Bedford-Fall River RI-MA	CBSA		
RURAL	RI				
ANDERSON	SC	Anderson, SC	City		
CHARLESTON	SC	Charleston, SC	City		
CHARLOTTE-GASTONIA-R HILL	SC	Charlotte-Gastonia-Concord NC-SC	CBSA		
COLUMBIA	SC	Columbia, SC	City		
FLORENCE	SC	Florence, SC	City		
GREENVILLE-SPARTANBURG	SC	Greenville-Mauldin-Easley SC	CBSA		
GREENVILLE-SPARTANBURG	SC	Spartanburg SC	CBSA		
RURAL	SC				
RAPID CITY	SD	Rapid City, SD	City		
SIOUX FALLS	SD	Sioux Falls, SD	City		
RURAL	SD				
CHATTANOOGA	TN	Chattanooga TN-GA	CBSA	MAG lists Chattanooga in two states	
CLARKSVILLE-HOPKINSVILL JACKSON	TN	Clarksville TN-KY	CBSA		
JOHNS CITY-KPORT-BRIST	TN	Jackson, TN	City		
JOHNS CITY-KPORT-BRIST	TN	Johnson City TN	CBSA	Kingsprt and Bristol are a separate CBSA	
KNOXVILLE	TN	Knoxville, TN	City		
MEMPHIS	TN	Memphis TN-MS-AR	CBSA		
NASHVILLE	TN	Nashville, TN	City		
RURAL	TN				
ABILENE	TX	Abilene, TX	City		
AMARILLO	TX	Amarillo, TX	City		
AUSTIN	TX	Austin, TX	City		
BEAUMONT-PORT ARTHUR	TX	Beaumont-Port Arthur TX	CBSA		
BRASORIA	TX	Brazoria, TX	City		
BROWNSVILLE-HARLINGEN	TX	Brownsville-Harlingen TX	CBSA		
BRYAN-COLLEGE STATION	TX	College Station-Bryan TX	CBSA		
CORPUS CHRISTI	TX	Corpus Christi, TX	City		
DALLAS	TX	Dallas, TX	City		
EL PASO	TX	El Paso, TX	City		
FORT WORTH-ARLINGTON	TX	Fort Worth-Arlington, TX	CBSA Div		
GALVESTON-TEXAS CITY	TX	Galveston, TX	City	Galveston and Texas City are listed as cities. No gap between cities.	
GALVESTON-TEXAS CITY	TX	Texas City, TX	City		
HOUSTON	TX	Houston, TX	City		

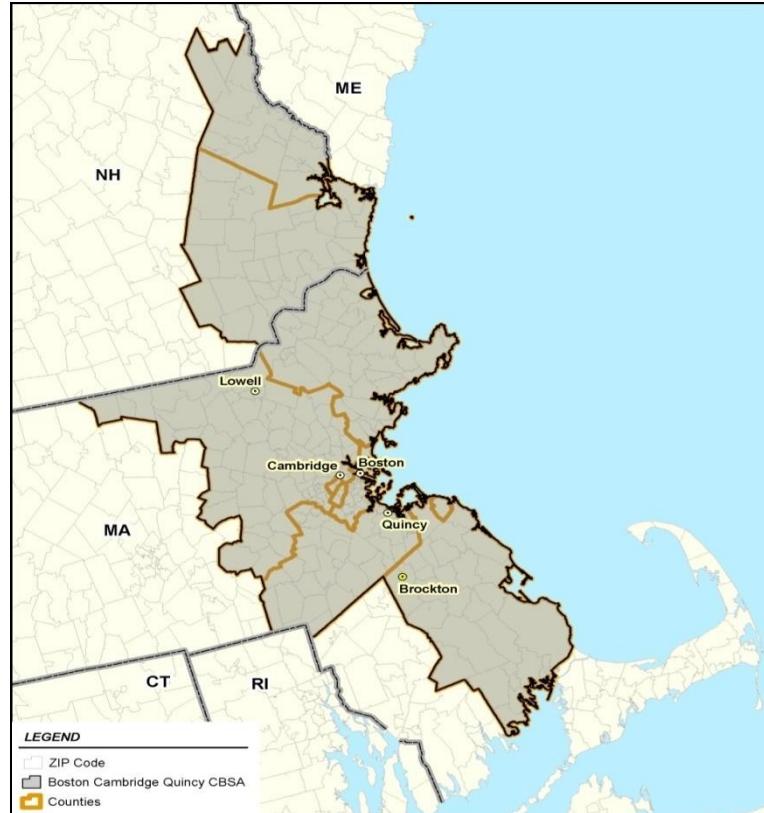
MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
KILLEEN-TEMPLE	TX	Killeen-Temple-Fort Hood TX	CBSA		
LAREDO	TX	Laredo, TX	City		
LONGVIEW-MARSHALL	TX	Longview TX	CBSA	Marshall is its own CBSA	
LONGVIEW-MARSHALL	TX	Marshall TX	CBSA		
LUBBOCK	TX	Lubbock, TX	City		
MCALLEN-EDINBURG-MISSION	TX	McAllen-Edinburg-Mission TX	CBSA		
MIDLAND	TX	Midland, TX	City		
ODESSA	TX	Odessa, TX	City		
SAN ANGELO	TX	San Angelo, TX	City		
SAN ANTONIO	TX	San Antonio, TX	City		
SHERMAN-DENISON	TX	Sherman-Denison TX	CBSA		
TEXARKANA	TX	Texarkana, TX	City		
TYLER	TX	Tyler, TX	City		
VICTORIA	TX	Victoria, TX	City		
WACO	TX	Waco, TX	City		
WICHITA FALLS	TX	Wichita Falls, TX	City		
RURAL	TX				
PROVO-OREM	UT	Provo-Orem UT	CBSA		
SALT LAKE CITY-OGDEN	UT	Salt Lake City UT	CBSA		
RURAL	UT				
CHARLOTTESVILLE	VA	Charlottesville, VA	City		
DANVILLE	VA	Danville, VA	City		
LYNCHBURG	VA	Lynchburg, VA	City		
JOHN CITY-KGSPORT-BRISTOL	VA	Kingsport-Bristol-Bristol TN-VA	CBSA		
NFOLK-VIRGINIA BEACH-NWPT	VA	Virginia Beach-Norfolk-Newport News VA-NC	CBSA		
RICHMOND-PETERSBURG	VA	Richmond VA	CBSA		
ROANOKE	VA	Roanoke, VA	City		
WASHINGTON	VA	Washington-Arlington-Alexandria DC-VA-MD-WV	CBSA		
RURAL	VA				
BURLINGTON	VT	Burlington, VT	City		
RURAL	VT				
BELLINGHAM	WA	Bellingham, WA	City		
BREMERTON	WA	Bremerton, WA	City		
OLYMPIA	WA	Olympia, WA	City		
RICHLAND-KENNEWICK	WA	Kennewick-Richland-Pasco WA	CBSA		
SEATTLE	WA	Seattle, WA	City		
SPOKANE	WA	Spokane, WA	City		
TACOMA	WA	Tacoma, WA	City		
VANCOUVER	WA	Vancouver, WA	City		
YAKIMA	WA	Yakima, WA	City		
RURAL	WA				
APPLETON-OSHKOSH-NEENAH	WI	Appleton WI	CBSA		
APPLETON-OSHKOSH-NEENAH	WI	Oshkosh-Neenah WI	CBSA		
DULUTH	WI	Duluth MN-WI	CBSA	MAG lists Duluth in WI and MN	
EAU CLAIRE	WI	Eau Claire, WI	City		
GREEN BAY	WI	Green Bay, WI	City		
JANESVILLE-BELOIT	WI	Janesville WI	CBSA		
KENOSHA	WI	Kenosha, WI	City		
LA CROSSE	WI	La Crosse, WI	City		
MADISON	WI	Madison, WI	City		
MILWAUKEE	WI	Milwaukee, WI	City		
MINNEAPOLIS-ST. PAUL	WI	Minneapolis-St. Paul	CBSA		

MAG Original Collection Name	State	Relevant Name From Assignment	Assigned Classification	Notes	Added Zip Codes
RACINE	WI	Bloomington MN-WI			
SHEBOYGAN	WI	Racine, WI	City		
WAUSAU	WI	Sheboygan, WI	City		
RURAL	WI	Wausau, WI	City		
CHARLESTON	WV	Charleston, WV	City		
CUMBERLAND	WV	Cumberland MD-WV	CBSA	MAG lists Cumberland in WV and MD	
HUNTINGTON-ASHLAND	WV	Huntington-Ashland WV-KY-OH	CBSA		
PARKERSBURG-MARIETTA	WV	Parkersburg-Marietta- Vienna WV-OH	CBSA		
STEUBENVILLE-WEIRTON	WV	Weirton-Steubenville WV-OH	CBSA		
WHEELING	WV	Wheeling WV-OH	CBSA		
RURAL	WV				
CASPER	WY	Casper, WY	City		
CHEYENNE	WY	Cheyenne, WY	City		
RURAL	WY				

To illustrate the assignment of zip codes for several MAG collections, Figure B3 through Figure B6 provide examples of how the zip codes are designated in different scenarios based on the characteristics of the MAG collection name.

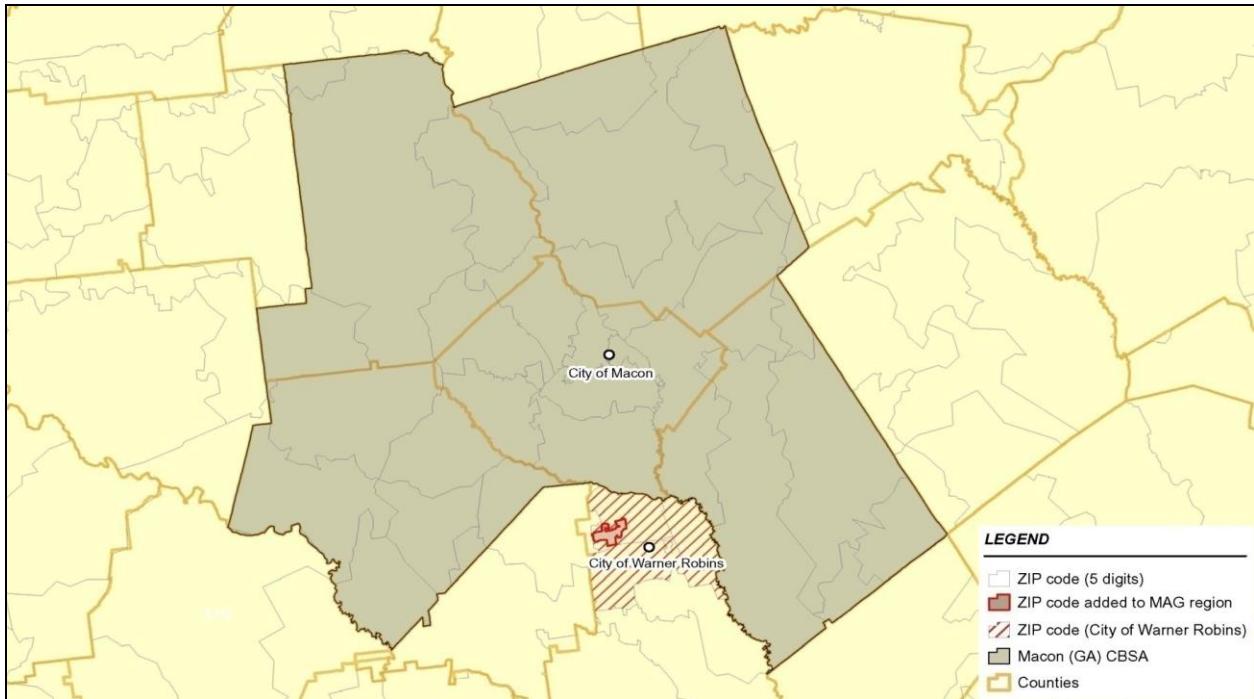
- 1) This first example demonstrates how a MAG collection name, Boston-Lowell-Brockton MA, is mapped to the Boston-Cambridge-Quincy CBSA. All three cities in the MAG collection are within the counties of the CBSA (Figure B3).

Figure B3 - Geographic referencing for MAG collection Boston-Lowell-Brockton MA



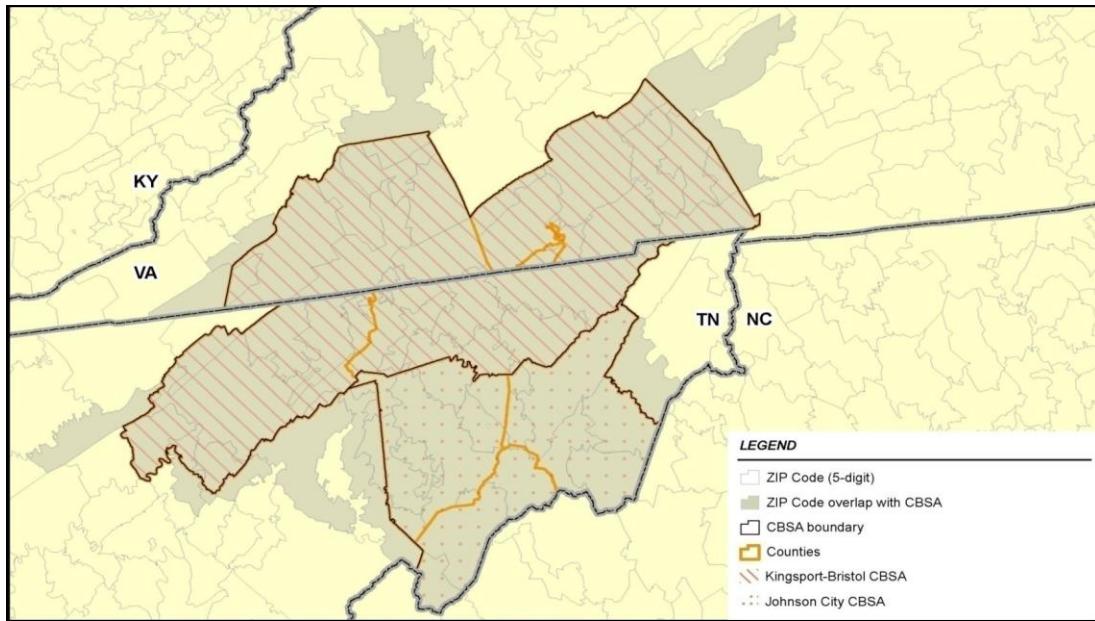
2) The second example displays a MAG region, Macon-Warner Robbins GA, mapping to a CBSA (Macon GA) and a city (Warner Robins). In this instance, there is a lone zip code surrounded by the Warner Robins city zip codes such that it is assigned to the MAG collection rather than the Rural GA designation (Figure B4).

Figure B4 - Geographic referencing for MAG collection Macon-Warner Robbins GA



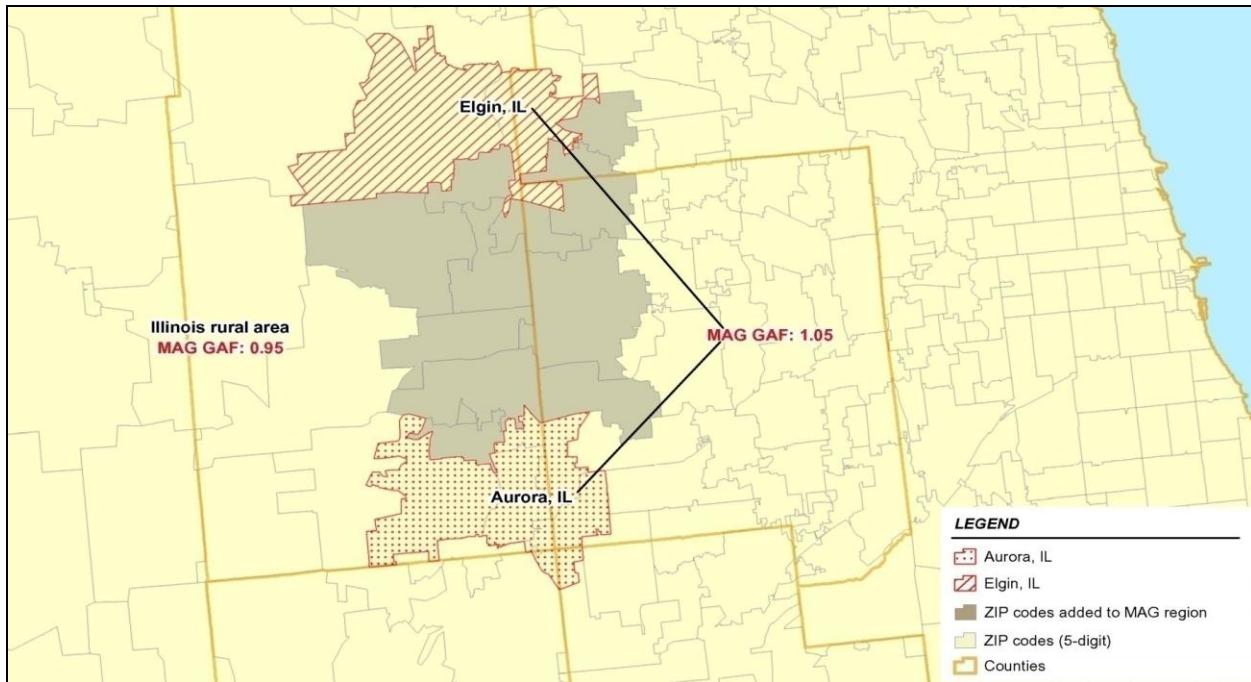
3) The third example demonstrates a MAG collection name, Johnson City-Kingsport-Bristol TN-VA, mapping to two CBSAs: Kingsport-Bristol TN-VA and Johnson City TN (Figure B5).

Figure B5 - Geographic referencing for MAG collection Kingsport-Bristol TN-VA & Johnson City TN



4) This last example shows the MAG collection name, Aurora-Elgin, IL, mapping to multiple cities, but not a CBSA. In this case, a convex set of zip codes between the two cities is assigned the Aurora-Elgin geographic adjustment factor rather than Rural, IL (Figure B6).

Figure B6 - Geographic referencing for MAG collection Aurora-Elgin, IL



Matching with Ingenix

MAG is matched to Ingenix based on CPT and geozip and adjusted for 5-digit zip codes (MAG.sas).

Coverage

Table B8 and Table B9 provide the percent of coverage by CPT, zip codes, CPT-by-geozips, claim and revenue of the comparison dataset relative to the datasets prepared for analysis.

Table B8 - 2005 Ingenix-MAG Coverage

2005	CPT	ZIPS	CPT-by-ZIP	Claims	Revenue
MAG	7,957	41,132	327,287,324		
Ingenix (all medical and surgical)	8,163	41,280	332,785,451	676,291,595	\$76,283,785,435
MAG-Ingenix comparison	5,464	41,049	59,503,750	630,621,559	\$ 67,296,780,574
% Coverage of Ingenix	66.9%		17.9%	93.2%	88.2%

Table B9 - 2006 Ingenix-MAG Coverage

2006	CPT	ZIPS	CPT-by-ZIP	Claims	Revenue
MAG	8,256	41,132	339,585,792		
Ingenix (all medical and surgical)	8,370	4,1203	340,987,793	747,243,081	\$87,188,761,656
MAG-Ingenix comparison	5,639	40,972	61,117,505	709,115,524	\$80,363,301,314
% Coverage of Ingenix	67.4%		17.9%	94.9%	92.2%

APPENDIX C: ADDITIONAL RESULTS

For those analyses where results for simple averages of matched pairs are presented in the report, this appendix presents their respective claim-weighted and dollar-weighted results. Conversely, for the analyses where claim-weighted results are presented in the report, the respective simple average and dollar-weighted results are presented here. For consistency, tables are numbered as in the report, with the addition of “A” for simple average, “B” for claim-weighted results or “C” for dollar-weighted results.

Table C-18B: Claim-weighted Percent Differences by AMA Section/Subsections

AMA Section/Subsection	Total Ingenix Claim Count	MAG	Medicare PSPS	PFR	PMIC
Medicine	260,471,368	-14%	8%	-12%	-1%
Evaluation & Management	208,802,147	5%	3%	8%	5%
Pathology, Lab	161,931,035	-8%	13%	1%	-1%
Radiology	28,621,031	-8%	11%	-3%	-7%
Cardiovascular	18,865,330	-17%	16%	-14%	1%
Integumentary	16,232,069	-2%	13%	-23%	0%
Musculoskeletal	5,349,731	10%	11%	7%	6%
Digestive System	3,838,609	-5%	12%	-2%	2%
Urinary	1,487,111	0%	4%	10%	0%
Endocrine, Nervous	1,475,400	12%	11%	12%	8%
Female Genital	1,382,532	0%	8%	6%	3%
Respiratory	1,235,178	-2%	9%	-3%	2%
Eye	988,552	-9%	101%	5%	0%
Maternity	934,024	-3%	11%	2%	1%
Ear	870,644	10%	7%	9%	8%
Male Genital	413,428	31%	11%	28%	11%
Lymphatic	109,639	15%	24%	53%	1%
Mediastinum	4,809	23%	13%	19%	16%

Table C-18C: Dollar-weighted Percent Differences by AMA Section/Subsections

AMA Section/Subsection	Total Ingenix Claim Count	MAG	Medicare PSPS	PFR	PMIC
Medicine	260,471,368	-8%	11%	-2%	3%
Evaluation & Management	208,802,147	7%	7%	15%	8%
Pathology, Lab	161,931,035	-2%	20%	14%	4%
Radiology	28,621,031	-6%	11%	1%	-3%
Cardiovascular	18,865,330	33%	17%	5%	4%
Integumentary	16,232,069	12%	16%	-5%	9%
Musculoskeletal	5,349,731	19%	23%	17%	15%
Digestive System	3,838,609	0%	16%	3%	7%
Urinary	1,487,111	33%	18%	19%	13%
Endocrine, Nervous	1,475,400	21%	22%	20%	20%
Female Genital	1,382,532	13%	14%	12%	9%
Respiratory	1,235,178	2%	15%	3%	8%
Eye	988,552	-6%	171%	0%	5%
Maternity	934,024	-1%	8%	4%	2%
Ear	870,644	30%	16%	18%	17%
Male Genital	413,428	29%	18%	29%	18%
Lymphatic	109,639	34%	36%	53%	22%
Mediastinum	4,809	39%	23%	34%	31%

Table C-19A: Simple Average Percent Differences for CPT 36471 across Benchmarks in 2006

CPT = 36471¹					
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴	
Alaska	1%	-34%	3%	-10%	
Michigan	2%	-10%	-4%	-36%	
Missouri	45%	-13%	38%	2%	
Virginia	18%	11%	25%	-1%	
Washington	20%	0%	19%	-2%	

Notes:

1. "Injection of sclerosing solution; multiple veins."
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table C-19C: Dollar-weighted Percent Differences for CPT 36471 across Benchmarks in 2006

CPT = 36471¹					
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴	
Alaska	2%	-34%	4%	-8%	
Michigan	13%	0%	5%	-30%	
Missouri	40%	4%	29%	5%	
Virginia	-3%	7%	9%	-10%	
Washington	23%	0%	23%	-2%	

Notes:

1. "Injection of sclerosing solution; multiple veins."
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table C-20A: Simple Average Percent Differences for CPT 97001 across Benchmarks in 2006

CPT = 97001¹					
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴	
Alabama	-6%	6%	-2%	-8%	
Connecticut	-5%	-1%	-2%	-6%	
Georgia	0%	-5%	-1%	-13%	
Nebraska	-10%	-18%	0%	-3%	
New Jersey	-1%	1%	6%	-6%	

Notes:

1. "Physical therapy evaluation."
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table C-20C: Dollar-weighted Percent Differences for CPT 97001 across Benchmarks in 2006

CPT = 97001¹				
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴
Alabama	0%	10%	6%	1%
Connecticut	-5%	2%	-3%	-7%
Georgia	2%	-3%	-4%	-16%
Nebraska	-3%	-13%	4%	0%
New Jersey	-3%	4%	3%	-5%

Notes:

1. "Physical therapy evaluation."
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table C-21A: Simple Average Percent Differences for CPT 99213 across Benchmarks in 2006

CPT = 99213¹				
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴
California	-5%	1%	2%	8%
Florida	12%	2%	2%	-9%
Mississippi	-1%	-1%	0%	-1%
West Virginia	4%	0%	3%	-17%

Notes:

1. "Office or other outpatient visit requiring an expanded problem-focused history."
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table C-21C: Dollar-weighted Percent Differences for CPT 99213 across Benchmarks in 2006

CPT = 99213¹				
State	MAG²	Medicare PSPS³	PFR⁴	PMIC⁴
California	0%	4%	6%	11%
Florida	11%	2%	4%	-8%
Mississippi	-1%	1%	0%	0%
West Virginia	5%	0%	3%	-17%

Notes:

1. "Office or other outpatient visit requiring an expanded problem-focused history."
2. Comparison of Ingenix 80th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. Comparison of Ingenix and Benchmark 75th percentile values.

Table C-22B: Claim-weighted Percent Differences of Matches for Subject Counties and Subject CPT Codes Identified in the NYAG Report, 2007

County	NYAG Report*	MAG		PFR		PMIC	
		80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
Albany							
99211		9%	49%	2%	26%	24%	61%
99212		6%	19%	6%	10%	27%	25%
99213		3%	7%	8%	4%	24%	18%
99214		-7%	5%	5%	10%	15%	16%
99215		-9%	5%	5%	9%	14%	14%
99245		-4%	3%	22%	17%	20%	11%
Erie							
99211	-20%	-19%	-4%	-20%	-19%	-3%	3%
99212	-22%	-14%	-1%	-17%	-10%	-1%	2%
99213	-17%	-21%	-13%	-18%	-17%	-6%	-5%
99214	-19%	-20%	-9%	-12%	-6%	-4%	-1%
99215	-28%	-19%	-2%	-12%	1%	-4%	6%
99245	-26%	-23%	-17%	-9%	-6%	-10%	-11%
Monroe							
99211		0%	8%	1%	-10%	27%	18%
99212		0%	14%	-7%	3%	14%	21%
99213		-13%	-1%	-6%	-6%	11%	10%
99214		-8%	7%	7%	9%	20%	19%
99215		-3%	13%	7%	15%	21%	24%
99245		3%	4%	28%	16%	30%	14%
New York							
99211	-20%	72%	72%	71%	40%	86%	59%
99212	-17%	41%	70%	40%	50%	48%	52%
99213	-14%	29%	61%	29%	50%	31%	51%
99214	-10%	18%	38%	31%	39%	27%	31%
99215	-1%	26%	27%	24%	27%	20%	18%
99245	0%	-1%	8%	15%	18%	1%	0%
Onondaga							
99211	-1%	14%	-7%	-7%	12%	18%	
99212	5%	12%	1%	-1%	19%	12%	
99213	-5%	4%	-3%	-4%	10%	9%	
99214	-7%	6%	4%	7%	14%	12%	
99215	1%	4%	8%	3%	17%	8%	
99245	-12%	-7%	8%	2%	6%	-4%	

Notes:

* See NYAG Report.

Table C-22C: Dollar-weighted Percent Differences of Matches for Subject Counties and Subject CPT Codes Identified in the NYAG Report, 2007

County	NYAG Report*	MAG		PFR		PMIC	
		80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
Albany							
99211		9%	49%	2%	26%	24%	61%
99212		6%	19%	6%	10%	27%	25%
99213		3%	7%	8%	4%	24%	18%
99214		-7%	5%	5%	10%	15%	16%
99215		-9%	5%	5%	9%	14%	14%
99245		-4%	3%	22%	17%	20%	11%
Erie							
99211	-20%	-19%	-4%	-20%	-19%	-3%	3%
99212	-22%	-14%	-1%	-17%	-9%	-1%	3%
99213	-17%	-21%	-13%	-17%	-16%	-5%	-5%
99214	-19%	-20%	-9%	-12%	-6%	-3%	-1%
99215	-28%	-19%	-1%	-12%	2%	-4%	7%
99245	-26%	-23%	-17%	-8%	-6%	-10%	-11%
Monroe							
99211		0%	8%	1%	-10%	27%	18%
99212		0%	14%	-7%	3%	14%	21%
99213		-13%	-1%	-6%	-6%	11%	10%
99214		-8%	7%	7%	9%	20%	19%
99215		-3%	13%	7%	15%	21%	24%
99245		3%	4%	28%	16%	30%	14%
New York							
99211	-20%	72%	72%	71%	40%	86%	59%
99212	-17%	41%	70%	40%	50%	48%	52%
99213	-14%	29%	61%	29%	50%	31%	51%
99214	-10%	18%	38%	31%	39%	27%	31%
99215	-1%	26%	27%	24%	27%	20%	18%
99245	0%	-1%	8%	15%	18%	1%	0%
Onondaga							
99211	-1%	14%	-7%	-7%	12%	18%	
99212	5%	12%	1%	-1%	19%	12%	
99213	-5%	4%	-3%	-4%	11%	9%	
99214	-7%	6%	5%	7%	14%	12%	
99215	1%	4%	8%	3%	17%	8%	
99245	-12%	-7%	8%	2%	6%	-4%	

Notes:

* See NYAG Report.

Table C-23B: Claim-weighted Percent Differences of Matches for Subject CPT Codes Identified in the NYAG Report across NY State, 2007

	MAG		PFR		PMIC	
	80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
99211	22%	36%	13%	11%	20%	22%
99212	8%	25%	2%	11%	8%	12%
99213	-1%	14%	-1%	6%	0%	6%
99214	-7%	9%	3%	10%	-1%	2%
99215	-4%	7%	-1%	6%	-6%	-3%
99245	-14%	-2%	-1%	8%	-15%	-12%

Table C-23C: Dollar-weighted Percent Differences of Matches for Subject CPT Codes Identified in the NYAG Report across NY State, 2007

	MAG		PFR		PMIC	
	80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
99211	27%	40%	19%	14%	25%	25%
99212	11%	29%	5%	14%	10%	15%
99213	1%	17%	0%	9%	1%	8%
99214	-5%	11%	5%	12%	1%	3%
99215	-1%	9%	2%	8%	-3%	-1%
99245	-13%	-1%	0%	9%	-14%	-11%

Table C-24B: Claim-weighted Percent Differences of Matches Pooled across Subject CPT Codes Identified in the NYAG Report, 2007

	MAG		PFR		PMIC	
	80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
Albany	1%	9%	7%	7%	21%	19%
Erie	-20%	-10%	-16%	-13%	-5%	-3%
Monroe	-10%	3%	-3%	-1%	14%	13%
New York	27%	52%	31%	44%	32%	42%
Onondaga	-4%	5%	-1%	-1%	12%	10%
Statewide	-1%	14%	0%	7%	1%	6%

Table C-24C: Dollar-weighted Percent Differences of Matches Pooled across Subject CPT Codes Identified in the NYAG Report, 2007

	MAG		PFR		PMIC	
	80 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile
Albany	-1%	7%	7%	7%	20%	18%
Erie	-20%	-10%	-15%	-12%	-5%	-3%
Monroe	-10%	3%	-1%	0%	15%	14%
New York	24%	46%	29%	41%	28%	37%
Onondaga	-5%	5%	0%	0%	12%	10%
Statewide	-1%	15%	2%	10%	1%	6%



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ATTACHMENT 1

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Professional Profile

Dr. Robin Ann Cantor is a Principal in Exponent's Alexandria, VA office. She specializes in applied economics, environmental and energy economics, statistics, risk management, and insurance claims analysis. Prior to joining Exponent, she led the Liability Estimation practice at Navigant Consulting and assisted companies and financial institutions with analysis to better understand asbestos and other product liability exposures. Other positions she has held include: Principal and Managing Director of the Environmental and Insurance Claims Practice at LECG, LLC, Program Director for Decision, Risk, and Management Sciences, a research program of the National Science Foundation, and senior research appointments at Oak Ridge National Laboratory. Dr. Cantor has a faculty appointment in the Graduate Part-time Program in Engineering of the Johns Hopkins University. She was the President of the Society for Risk Analysis in 2002, and from 2001-2003, she served as an appointed member of the Research Strategies Advisory Committee of the US Environmental Protection Agency's Science Advisory Board. She is a member of the Executive Committee for the Women's Council on Energy and the Environment. Dr. Cantor's testimonial experience includes product liability estimation in bankruptcy matters and insurance disputes, statistical analysis of asbestos settlements, analysis of premises and product claims, cost contribution allocation in Superfund disputes, analysis of derailment risks, reliability of statistical models and estimation methods, and economic analysis of class certification issues. She has prepared expert reports that address economic issues in antitrust, intellectual property, employment discrimination, false advertising, regulation, and other areas of product and market analysis. Dr. Cantor has submitted analysis, testimony and affidavits in federal arbitration, regulatory and Congressional proceedings, and state and federal courts. Dr. Cantor's publications include refereed journal articles, book chapters, expert reports, reports for federal sponsors, and a book on economic exchange under alternative institutional and resource conditions.

Academic Credentials and Professional Honors

Ph.D., Economics, Duke University, 1985
B.S., Mathematics, Indiana University of Pennsylvania, 1978

Fellow, Society for Risk Analysis, 2002
President, Society for Risk Analysis, 2002
YWCA Tribute to Women Award for Business and Industry, 1990

Society for Risk Analysis Presidential Recognition Award, 2008; Society for Risk Analysis Outstanding Service Award, 1999; NSF Director's Award for Superior Accomplishment, 1996; NSF Special Act Award, 1995; NSF Director's Award for Program Officer Excellence, 1994; Oak Ridge National Laboratory Significant R&D Accomplishment Award, 1993; Martin Marietta Special Achievement Award, 1990; Martin Marietta Special Achievement Award, 1989; Martin

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Technical Manuscripts

Analysis of the Estimated Production Cost Savings From Replacing the Dollar Note with the Dollar Coin. Final report of analysis submitted to Congressional Record, June 12, 2000 (with Jessica B. Horewitz and Robert N. Yerman).

Rebuttal Verified Statement with Gordon C. Rausser for CSX Corporation and CSX Transportation, Inc., Norfolk Southern Corp., and Norfolk Southern Railway Co., Control and Operating Leases/Agreements, Conrail Inc. and Consolidated Rail Corp., Railroad Control Application, Applicants' Rebuttal Vol. 2B of 3, December, 1997.

Community Preferences and Superfund Responsibilities. Prepared for the USEPA under Interagency Agreement 1824-B067-A1 with Oak Ridge National Laboratory, August 1993.

The U.S.-EC Fuel Cycle Study: Background Document to the Approach and Issues. Oak Ridge National Laboratory, ORNL/TM-2500, November, 1992 (with L. W. Barnthouse, D. Burtraw (Resources for the Future), G. F. Cada, C. E. Easterly, A. M. Freeman (Bowdoin College), W. Harrington (Resources for the Future), T.D. Jones, R. L. Kroodsma, A. J. Krupnick (Resources for the Future), R. Lee, H. Smith (DOE), A. Schaffhauser, and R. S. Turner).

What are the Problems of Equity and Legitimacy Facing a Management Strategy for the Global Commons? Managing the Global Commons: Decision Making and Conflict Resolution in Response to Climate Change, Oak Ridge National Laboratory, ORNL/TM-11619, July, 1990 (with Roger Kasperson in Steve Rayner, Wolfgang Naegeli, and Patricia Lund).

Markets, Distribution, and Exchange after Societal Cataclysm, Oak Ridge National Laboratory, ORNL-6384, November 1989 (with S. Rayner and S. Henry).

Information. Chapter 5 of A Compendium of Options for Government Policy to Encourage Private Sector Responses to Potential Climate Change, DOE/EH-0102, Report to Congress, October, 1989 (with G. G. Stevenson and P. J. Sullivan).

Agriculture and Forestry. Chapter 10 of A Compendium of Options for Government Policy to Encourage Private Sector Responses to Potential Climate Change, DOE/EH-0102, Report to Congress, October, 1989 (with W. Naegeli and A. F. Turhollow, Jr.).

Evaluation of Implementation, Enforcement and Compliance Issues of the Bonneville Model Conservation Standards Program, Vol. I and II, ORNL/CON-263, July 1989 (with Steve Cohn).

Gas Furnace Purchases: A Study of Consumer Decision Making and Conservation Investments. ORNL/TM-10727, October 1988 (with David Trumble).

An Analysis of Nuclear Power Plant Construction Costs. DOE/EIA-0485, 1986 (with J. G. Hewlett and C. G. Rizy).

Nuclear Reactor Decommissioning: A Review of the Regulatory Environments. ORNL/TM-9638, 1986.

Nuclear Power Options Viability Study, Vol. I, Executive Summary, ORNL/TM-9780/1, 1986 (with D. B. Trauger et al.).

Nuclear Power Options Viability Study, Vol III, Nuclear Discipline Topics. ORNL/TM-9780/3, 1986 (with D. B. Trauger et al.).

Clinch River Breeder Reactor: An Assessment of Need for Power and Regulatory Issues, ORNL/TM-8892, September 1983 (with D. M. Hamblin et al.).

Selected Presentations

Cantor RA. Evaluating vulnerabilities and identifying emerging risks. Invited presentation, The Conference Board EHS Legal Counsel Meeting, Houston TX, January 15–16, 2009.

Cantor RA. Using exposure science to ascertain asbestos liabilities. Invited CLE presentation, Business Valuation Resources, LLC Teleconference, November 18, 2008.

Cantor RA. Weather and temperature: Emerging health issues for US companies. REBEX 2008, Wheeling IL, October 23–24, 2008.

Cantor RA. Asbestos risk transfers: Unlocking value by walling off asbestos liabilities. Invited CLE session at Willkie Farr & Gallagher, New York, NY, June 4, 2008.

Cantor RA. The future of asbestos—New techniques for unlocking value by selling liabilities to investors. Mealey's™ Teleconference, March 25, 2008.

Cantor RA. Update on other U.S. long-tailed product liabilities. Invited presentation, 4th International Asbestos Claims & Liabilities Conference: The Practical Guide to Litigating, Settling and Managing Asbestos Claims, London, January 30–31, 2008.

Cantor RA. Tax or cap: What are the real differences for carbon policy in the US? Invited session and presentation, McDermott Will & Emery 10th Annual Energy Conference, Washington DC, October 9–10, 2007.

Cantor RA. Managing nanotechnology's life cycle risks responsibly. Invited ALI-ABA teleconference, June 27, 2007.

Cantor RA. Carbon emissions—Planning for the change. Invited teleconference, Environmental Law Network, June 15, 2007.

Cantor RA. Liability estimation and the historical future. Invited presentation, Mealey's™ Asbestos Bankruptcy Conference, Chicago, IL, June 7–8, 2007.

Cantor RA. Renewables and the value proposition for carbon credits. Invited presentation, McDermott Will & Emery 9th Annual Energy Conference, Washington DC, October 19–20, 2006.

Cantor RA. The ABCs of the value proposition for carbon credits. Invited presentation, the Environmental Trading Congress, New York, NY, July 24–25, 2006.

Cantor RA, Lyman M. Liability estimation in U.S. bankruptcy cases. London Underwriting Centre, London, UK, January 10, 2006.

Cantor RA, Lyman M. The status of the FAIR Act. London Underwriting Centre, London, UK, January 10, 2006.

Cantor RA. Economic appraisal of ecological assets. Invited presentation, U.S. Environmental Protection Agency Science Advisory Board "Science and the Human Side of Environmental Protection" Series, Washington, DC, July 6, 2002.

Cantor RA. Scientists and Homeland Security—The relevance of risk analysis. Invited presentation, Council of Scientific Society Presidents, Washington, DC, May 2002.

Cantor RA. NRD rules and economics. Invited presentation, Environmental and Admiralty Law Committees of the Association of the Bar of the City of New York, December 7, 2000.

Cantor RA. Revealed preferences and environmental risks: Lessons learned from two policy debates. Annual Meetings of the Society For Risk Analysis, Phoenix, AZ, December 8, 1998.

Cantor RA. Valuing environmental impacts: Lessons learned from the natural resource damage debate. Invited Paper, Society of Environmental Toxicology and Chemistry, 19th Annual Meeting, November 19, 1998.

Cantor RA. How will climate change affect economics and politics? Invited panel speaker, Policy and Politics of Climate Change, ABA Section of Natural Resources, Energy, and Environmental Law Fall Meeting, October 8, 1998.

Cantor RA. Natural resource damage rules: A search for the path of least resistance in value disputes? George Washington University Seminar Series on Environmental Values and Strategies, September 1997.

Cantor RA. Rethinking the science of risk management: Changing paradigms of the process and function. Operations and Information Management Department Workshop, Wharton School of the University of Pennsylvania, November 1995.

Cantor RA, Arkes H. Interdisciplinary perspectives on experimental methods. 1995 Meetings of the American Economic Association, January 1995.

Cantor RA. Risk management: Four different views. Invited presentation, The Conservation of Great Plains Ecosystems Symposium, April 1993.

Cantor RA. Human dimensions of global change: A white paper on the USGCRP research programs. National Academy of Sciences Board on Global Change, November 1993.

Cantor RA, Rayner S. Changing perceptions of vulnerability. Invited paper, NCAR/UCAR Summer Institute on Industrial Ecology and Global Change, July 17–31, 1992.

Cantor RA. Should economic considerations limit the conservatism of risk assessment? Invited paper, Workshop of the International Society of Regulatory Toxicology and Pharmacology on Risk Assessment and OMB's Report on its Application in Regulatory Agencies, Washington, DC, June 11, 1991.

Cantor RA. Beyond the market: Recent regulatory responses to the externalities of energy production. Annual Meetings of the National Association of Environmental Professionals, Baltimore, MD, April 30, 1991.

Cantor RA. Understanding community preferences at Superfund sites. National Meeting of EPA Community Relations Coordinators, Chicago, IL, April 4–6, 1990.

Cantor RA. Methodological myths and modeling markets: A common framework for analyzing exchange. Second Annual International Conference on Socio-Economics, Washington, DC, March 1990.

Cantor RA, Schoepfle GM, Szarleta EJ. Sources and consequences of hypothetical bias in economic analyses of risk behavior. 1989 Meetings of Society for Risk Analysis, October 1989.

Cantor RA, Jones D, Lieby P, Rayner S. Policies to encourage private sector responses to potential climate change. 1989 Meetings of International Association of Energy Economists, October 1989.

Cantor RA, Szarleta EJ. The experimental approach in public policy analysis: precepts and possibilities. Public Choice Society and Economic Science Association Annual Meetings, Orlando, FL, March 17–19, 1989.

Cantor RA, Rayner S. Global disaster management: Developing principles for research. 1988 Meetings of the Association for Public Policy Analysis and Management, October 1988.

Cantor RA. Implementation and enforcement issues from early adopter experience. Regional Evaluation Network, Northwest Power Planning Council, Portland, OR, June 1988.

Cantor RA. Using information from toxic-tort litigation to value the health and safety consequences of regulatory decisions. Public Policy Workshop, the Department of Economics and Waste Management Research and Education Institute, University of Tennessee, Knoxville, TN, February 1988.

Cantor RA, Bishop R, Jr. Valuing safety and health effects in regulatory decisions: A revealed-preference approach. 1987 Annual Meeting of the Society for Risk Analysis, November 3, 1987.

Cantor RA. Government intervention and technology prices: The CANDU example. Invited paper, WATTEC Conference, Knoxville, TN, February 19, 1987.

Cantor RA. Fairness hypothesis and managing the risks of societal technology choices. 1986 Winter Annual Meeting of the American Society of Mechanical Engineers, Anaheim, CA, December 10–12, 1986.

Cantor RA. A retrospective analysis of technological risk: The case of nuclear power. Invited paper, Center of Resource and Environmental Policy Workshop Series, Vanderbilt University, Nashville, TN, December 4, 1986.

Cantor RA, Petrich C, Mercier J-R. Evaluation of a large-scale charcoal project in Madagascar: Attacking the deforestation problem from the supply side. 1986 IAEE North American Conference, Cambridge, MA, November 19–21, 1986.

Cantor RA, Rayner S. Tools for the job: Choosing appropriate strategies for risk management. 1986 Annual Meeting of the Society for Risk Analysis, Boston, MA, November 9–12, 1986.

Cantor RA, Rayner S. Thinking the unthinkable: Preparing for global disaster. 1986 Annual Meeting of the Society for Risk Analysis, Boston, MA, November 9–12, 1986.

Cantor RA, Rayner S, Braid B. The Role of liability preferences in societal technology choices: Results of a pilot study. 1985 Annual Meetings of Society for Risk Analysis, Washington, DC, October 8, 1985.

Conference Participation

Invited panelist for “An Integrated Risk Framework for Gigawatt-Scale Deployments of Renewable Energy: The Wind Energy Case Study,” 2009 Annual Meeting for the Society for Risk Analysis, Baltimore, MD, December 9, 2009.

Invited session organizer and panelist for “Global Warming and Greenhouse Gas Controls: What do they mean for you?” 2008 Annual Meeting of the National Association of Publicly Traded Partnerships, Washington DC, June 26, 2008.

Co-chair, “Second World Congress on Risk,” Guadalajara, Mexico, June 2008.

Invited panelist for “Climate Litigation: The Next Asbestos or the Next Y2K?” ABA Section of Litigation Annual Conference, Washington DC, April 17, 2008.

Invited panelist for “Business of Mitigation: Carbon Offsets and Trading,” Oxford University Capstone Conference, Oxford, UK, September 10, 2007.

Panelist for “Issues Concerning Implementation,” at the Public Forum on OMB’s Proposed Risk Assessment Bulletin: Implications for Practice Inside and Outside Government, sponsored by Society for Risk Analysis, Society of Environmental Toxicology and Chemistry in North America, Society of Toxicology, and International Society of Regulatory Toxicology and Pharmacology.

Session Chair, “Challenges Facing Industrial Countries,” with key-note speeches by Philippe Busquin, EU Commissioner for Research, and Dr. John Graham, Administrator of the US Office of Information and Regulatory Affairs, Inaugural Conference of the International Risk Governance Council, Geneva, Switzerland, June 29, 2004.

Co-Chair, “First World Congress on Risk,” Brussels, Belgium, June 2003.

Chair of the Organizing Committee, 2001 Annual Meetings for the Society for Risk Analysis.

Member of the Organizing Committee, Risk and Governance Symposium, Society for Risk Analysis, June 2000.

Organizing Committee Member for the 1996, 1997, 1998, and 2002 Annual Meetings of the Society for Risk Analysis.

Panelist for Net Environmental Benefits Assessment for Restoration Projects after Oil Spills, Conference on Restoration for Lost Human Uses of the Environment, Washington, DC, May 1997.

Session Organizer and Chair for Cost Benefit Analysis and Risk Assessment at the 1996 Annual Meeting of the Society for Risk Analysis.

Panelist for Challenges in Risk Assessment and Risk Management sponsored by The Annenberg Public Policy Center of the University of Pennsylvania at the National Press Club, Washington, DC, May 16, 1996.

Panelist for Media and Risk in a Democracy: Who Decides What Hazards Are Acceptable? At the 1995 Annual convention of the Association for Education in Journalism and Mass Communication.

Session Organizer and Co-Chair for Experimental Methods: Insights from Economics and Psychology at the 1995 Meetings of the American Economic Association.

U.S. Organizer for the Third Japan-U.S. Workshop on Global Change Modeling and Assessment: Improving Methodologies and Strategies, Hawaii, October 1994.

Cluster Organizer for three sessions on Competitiveness at the Fall Meeting of the Operations Research Society of America/The Institute of Management Sciences, 1994.

Roundtable Panelist for Risk Communication Research: Defining Practitioner Needs at the 1994 Meetings of the Society for Risk Analysis.

Workshop Organizer for Organizational Transformation and Quality Systems, National Science Foundation, 1993.

Session Chair and Organizer for the NSF/Private Sector Research Initiative Projects at the 1992 Meetings of the Society for Risk Analysis.

Roundtable Panelist for the EPA Session on Risk Communication at the 1990 Meetings of the Society for Risk Analysis.

Session Chair and Organizer for the Computer Assisted Market Institutions Session at the Advanced Computing for the Social Sciences Conference, April 1990.

Discussant for the Issues in LDC Public Finance Session at the 1988 Meetings of the American Economic Association.

Session Chair and Organizer for Social Science Innovations in Risk-Analysis Methods, Special Session at the 1988 Meetings of the Society for Risk Analysis.

Prior Experience

Managing Director, Navigant, 2004–2008

Lecturer, Graduate Program, Johns Hopkins University, Engineering and Applied Science Programs for Professionals, Program in Environmental Engineering, Science and Management, 1996–present

Principal and Managing Director, LECG, 1999–2004

Senior Managing Economist, LECG, 1999

Managing Economist, LECG, 1996–1998

Member, U.S. Environmental Protection Agency, Science Advisory Board, Research Strategies Advisory Committee, 2001–2003

Program Director, Decision, Risk, and Management Science, National Science Foundation, 1992–1996

Coordinator, NSF Human Dimensions of Global Change, 1992–1996

Project Manager, Oak Ridge National Laboratory, 1990–1991

Technical Assistant to the Associate Director, Advanced Energy Systems, Oak Ridge National Laboratory, 1989–1990

Group Leader, Social Choice and Risk Analysis Group, Energy and Economic Analysis Section, Oak Ridge National Laboratory, June 1987–1989

Research Staff, Energy and Economic Analysis Section, Oak Ridge National Laboratory, Oak Ridge National Laboratory, October 1982–1987

Consultant, Indonesian Energy Project, Harvard Institute For International Development, July 1987

Visiting instructor, North Carolina Central University, Spring 1982

Advisory and Other Appointments

- National Research Council Committee to Review the Department of Homeland Security's Approach to Risk Analysis, November, 2008–present
- Executive Committee, Women's Council on Energy and the Environment, 2006–present
- Board Member, Women's Council on Energy and the Environment, 2004–2006
- Member, Advisory Group for the Joint Global Change Research Institute, a collaboration between Pacific Northwest National Laboratory and the University of Maryland, 2004–present
- Member, Planning Committee for a study to evaluate the U.S. National Assessment of the Potential Consequences of Climate Variability and Change, coordinated through Carnegie Mellon University, 2004
- Neutral technical panelist working with Arbitrator Anthony Sinicropi on negotiation issues related to the pilots' compensation contract. Retained by US Airways and the Air Line Pilots Association (ALPA), 2001 and 2002
- Advisory Board Member, Johns Hopkins University Graduate Part-Time Program in Environmental Engineering and Science
- Planning Committee Member, Carnegie Council on Ethics and International Affairs Long Term Study of Culture, Social Welfare, and Environmental Values in the U.S., China, India, and Japan, initiated January 1997

- Vice-Chair, U.S. Global Change Research Program working group on Assessment Tools and Policy Sciences, 1994–1996
- US Federal Reviewer for the Intergovernmental Panel on Climate Change working group III 1995 Report on Socioeconomics
- NSF Principal for the Committee on the Environment and Natural Resources' Subcommittee on Risk Assessment, 1993–1996. Also served as the liaison between the Subcommittee on Risk Assessment and the Subcommittee on Social and Economic Sciences
- Advisory panel member for Environmental Ethics and Risk Management, National Academy of Public Administration and George Washington University, 1993–1994
- Science Advisory Board member for Consortium for International Earth Science Information Network, 1993
- Review Panel member for Economics and the Value of Information, NOAA, 1993
- NSF technical representative to the FCCSET Ad Hoc Working Group on Risk Assessment and member of its Subcommittee on Risk Assessment, 1992–1993
- NSF representative to Working Party of the FCCSET Subcommittee for Global Change Research on Assessment, 1992–1993
- Affirmative Action Representative for the Energy Division, Oak Ridge National Laboratory 1984–1989, AA Rep for the Central Management Organization of ORNL, October 1989 to November 1990
- Board of Directors, Vice President (1987–1988), President (1988–1989), Matrix Organization, The Business Center for Women and Minorities, Knoxville, TN

Editorships and Editorial Review Boards

- Editorial Board, *Journal of Risk Analysis*, 1997–present
- Editorial Board, *Journal of Risk Research*, 1997–2005

Peer Reviewer

- The Energy Journal, Climate Change, Contemporary Economic Policy, Growth and Change, Ecological Applications, Risk Analysis, Duke University Press, Princeton University Press, J. of Environmental Economics and Management, Resources and Energy, The Environmental Professional, Journal of Risk Research, National Science Foundation, National Oceanic and Atmospheric Administration, FORUM, U.S. Environmental Protection Agency

Professional Affiliations

- American Economic Association
- Women's Council on Energy and the Environment
- Society for Risk Analysis
 - President, Society for Risk Analysis, 2002
 - President-Elect, Society for Risk Analysis, 2001
 - Councilor, Society for Risk Analysis, 1996–1999
- American Bar Association

Deposition /Trial Testimony

Available on request



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Alexandria, VA 22314

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facsimile 571-227-7299
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ATTACHMENT 2: CANTOR TESTIMONY

Robin A. Cantor, Ph.D.
Principal

EXPERT TESTIMONY

In re USG Corporation et al. Debtors

Stroock & Stroock & Lavan (Official Committee of Unsecured Creditors)
• Declaration (August, 2005)

In the Matter of the Rehabilitation of the Centaur Insurance Company

Office of Special Deputy Receiver and Sidley Austin LLP (Centaur Insurance)
• Deposition (April, 2006)

Class Plaintiffs v. American Heritage Life Insurance Company et al.

Polsinelli Shalton Welte Suelthaus PC and King & Spalding (Defendants)
Missouri state court (03-CV-233109)
• Affidavit (October, 2006)

Class Plaintiffs v. American Express Company and American Express Travel Services Company, Inc.

Friedman Law Group LLP (Plaintiffs)
US District Court Southern District of New York (04 Civ. 05432 (GBD))
• Declaration (November, 2007)
• Deposition (November, 2007)
• Reply Declaration (March, 2008)

In the Matter of Dana Corporation, Debtors.

Jones Day (Debtor)
US Bankruptcy Court, Southern District of New York
• Trial Testimony (December, 2007)

In re Packaged Ice Antitrust Litigation

Spector, Roseman, Kodroff & Willis, P.C. (Class Plaintiffs)
Case No. 2:08-md-01952 (PDB) MDL No. 1952
US District Court for the Eastern District of Michigan
• Declaration (December, 2008)

**The Howard Hughes Properties and Howard Hughes Corporation v. Kern River Gas
Transmission Company**

Bracewell & Giuliani LLP (Plaintiffs/Counterdefendants)

Case No. 2:09-cv-00657-RLH-LRL

US District Court, District of Nevada

- Affidavit (October, 2009)
- Deposition (December, 2009)

TYR Sport Inc. v. Warnaco Swimwear Inc. dba Speedo USA

O'Neil LLP (Plaintiffs/Counterdefendants)

Case No. SACV 08-529-JVS(MLGx)

US District Court for the Central District of California

- Declaration (March, 2010)
- Declaration (April, 2010)

ATTACHMENT 3: MATERIALS CONSIDERED

I. LEGAL DOCUMENTS

A. Complaints

First Amended Class Action Complaint, Weintraub v. Ingenix, Inc. et al. (D. Conn. Filed Aug. 15, 2008).

Joint Consolidated Amended Class Action Complaint and Demand for Jury Trial, In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation (MDL No. 2020 filed Jul. 1, 2009).

Third Amended Class Action Complaint, Cooper et al. v. Aetna Health Inc. PA, Corp. et al., (D.N.J. filed Feb. 28, 2008).

B. Depositions

Deposition Transcript of Brian Mullins (Feb. 22, 2010).

Deposition Transcript of Carla Gee.

Deposition Transcript of Carmen Kavali (Feb. 12, 2010).

Deposition Transcript of Carolyn Samit (Feb. 2, 2010).

Deposition Transcript of Darlery Franco (Jan. 22, 2010).

Deposition Transcript of Darrick Antell (Mar. 9, 2010).

Deposition Transcript of Frank Tonrey.

Deposition Transcript of James Cross (Mar. 23, 2010).

Deposition Transcript of Jeffrey M. Weintraub (Mar. 1, 2010).

Deposition Transcript of Michelle Cooper (Jan. 19, 2010).

Deposition Transcript of Michelle Lynn Werner (Jan. 25, 2010).

Deposition Transcript of Paul Smith (Jan. 20, 2010).

Deposition Transcript of Sharon Smith (Jan. 21, 2010).

C. Expert Reports

Expert Report of Bernard R. Siskin, Ph.D., Wachtel v. Health Net, McCoy v. Health Net (Mar. 31, 2004).

Supplemental Expert Report of Bernard R. Siskin, Ph.D., Wachtel v. Health Net, McCoy v. Health Net (Jun. 15, 2006).

D. Interrogatories

Aetna Answers and Objections to Plaintiffs’ First Set of Interrogatories, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Jun. 4, 2008).

Aetna’s Answers and Objections to Plaintiffs’ Second Set of Interrogatories, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 3, 2008).

Aetna’s Supplemental Responses and Objections to Plaintiffs’ First Set of Interrogatories (Interrogatory Nos. 1-7, 8, 10, 14, 15, 24), Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 24, 2008)

Plaintiff Angela Hull’s Responses and Objections to Aetna’s Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 13, 2010).

Plaintiff Carolyn Samit's Response to Aetna Defendants' Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010).

Plaintiff Carolyn Whittington's Response to Aetna Defendants' Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010).

Plaintiff Darlery Franco's Response to Aetna Defendants' Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010).

Plaintiff Darlery Franco's Response to Aetna's First Set of Interrogatories, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Jun. 6, 2008).

Plaintiff Jeffrey M. Weintraub's Responses and Objections to Aetna's Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 13, 2010).

Plaintiff Michele Cooper's Response to Aetna Defendants' Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010).

Plaintiff Michele Cooper's Response to Aetna's First Set of Interrogatories, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Jun. 6, 2008).

Plaintiff Michele Werner's Response to Aetna Defendants' Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010)

Plaintiff Paul and Sharon Smith's Response to Aetna Defendants' Second Set of Interrogatories, In Re: Aetna UCR Litigation (Jan. 18, 2010).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Darrick C. Antell, MD, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Carmen Kavali, MD, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Abraham I. Kozma, PA, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Maldonado Medical, LLC, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Brian Mullins, PT, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Alan B. Schorr, MD, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28. 2009).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Frank G. Tonrey, MD, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiff's Objections and Responses to Defendants' First Set of Interrogatories to Plaintiff Jeffrey M. Weintraub, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiff's Objections to Responses to Defendants' First Set of Interrogatories to Plaintiff Angela Hull, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Oct. 28, 2009).

Plaintiffs Paul and Sharon Smith's Response to Defendants' First Set of Interrogatories, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Jul. 16, 2009).

Plaintiffs' First Set of Interrogatories, Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Apr. 30, 2008).

Plaintiffs' Objections and Responses to Aetna's Second Set of Interrogatories to Provider Plaintiffs, In Re: Aetna UCR Litigation (Jan. 13, 2010).

Plaintiffs' Second Set of Interrogatories (These Interrogatories are Specific to Outdated Data), Cooper, et al. v. Aetna Health Inc. PA, Corp., et al. (Jul. 22, 2008).

E. Motions and Supporting Memoranda

Defendants' Brief in Opposition to Plaintiff's Motion for Class Certification, McCoy v. Health Net, Inc., et al. (Apr. 14, 2004)

Memorandum of Law in Support of Defendants' Motion to Dismiss Plaintiffs' Third Amended Complaint, Cooper et al. v. Aetna Health Inc. PA, Corp., et al. (Mar. 26, 2008).

Plaintiffs' Corrected Memorandum of Law in Opposition to Defendants' Motion to Dismiss Plaintiffs' Third Amended Class Action Complaint, Cooper et al. v. Aetna Health Inc. PA, Corp., et al. (Apr. 15, 2008).

Reply Brief in Support of Defendants' Motion to Dismiss Plaintiffs' Third Amended Complaint, Cooper et al. v. Aetna Health Inc. PA, Corp., et al. (Apr. 25, 2008).

Reply Memorandum of Law on Behalf of Plaintiffs Renee McCoy and Zev and Linda Wachtel in Further Support of Plaintiffs' Motion for Class Certification, McCoy v. Health Net, Inc., Wachtel v. Health Net, Inc., et al. (May 4, 2004).

F. Miscellaneous

Case Management Order No. 1, In Re: Aetna UCR Litigation (MDL No. 2020 filed Jun. 15, 2009).

Case Management Order No. 3, In Re: Aetna UCR Litigation (MDL No. 2020 filed Dec. 11, 2009).

Case Management Order No. 4, In Re: Aetna UCR Litigation (MDL No. 2020 filed Feb. 1, 2010).

In Re Adoption of N.J.A.C. 11:3-29 by the State of New Jersey, Department of Banking and Insurance, No. A-0344-07T3 (N.J. Super. Ct. App. Div. filed Aug. 10, 2009).

Joint Statement Regarding the April 10, 2008 Evidentiary Hearing of the Ingenix Database, McCoy v. Health Net, Inc., et al., Wachtel v. Health Net, Inc., et al., Scharfman, et al. v. Health Net, Inc., et al. (Apr. 8, 2008).

Opinion, McCoy v. Health Net, Inc., et al., Wachtel, et al. v. Health Net, Inc., et al., and Scharfman, et al. v. Health Net, Inc., et al. (D.N.J. filed Aug. 8, 2008).

Opinion, Wachtel v. Guardian Life Ins. Co., et al., McCoy v. Health Net, Inc., et al. (D.N.J. filed Aug. 5, 2004).

Order on Informal Application & Second Amended Pretrial Scheduling Order, Cooper et al. v. Aetna Health Inc. PA, Corp. et al. (Sep. 10, 2008).

Stipulation Regarding Expert Disclosures, In Re: Aetna UCR Litigation (Dec. 4, 2009).

Transfer Order, In re Aetna, Inc., Out-Of-Network "UCR" Rates Litigation (MDL No. 2020 filed Apr. 8, 2009).

G. Request for Production of Documents

Aetna's Responses and Objections to Plaintiffs' Amended First Set of Requests, Cooper et al. v. Aetna Health Inc. PA, Corp. et al. (Nov. 7, 2008).

Plaintiffs' Amended First Set of Document Requests (Revised Instructions), Cooper et al. v. Aetna Health Inc. PA, Corp. et al. (Sep. 16, 2008).

H. Trial Transcripts

Examination before Trial of Deborah Justo, McCoy v. Health Net, Inc., et al., Wachtel v. Guardian Life Insurance Company of America, et al. (Apr. 14, 2005).

Examination before Trial of Sharon Chilcott, McCoy v. Health Net, Inc., et al., Wachtel v. Guardian Life Insurance Company of America, et al. (Apr. 14, 2005).

Transcript of Proceedings (Siskin), Wachtel v. Guardian Life, et al., McCoy v. Health Net, Inc., et al. (Apr. 10, 2008).

II. BATES-STAMPED DOCUMENTS

AET-00005627 – AET-00005676

AET-00296986 – AET-00296989

AET-00297108 – AET-00297210

AET-00613695 – AET-00613698

AET-03582477 – AET-03582517

AET-03582477 – AET-03582517

AET-03582589 – AET-03582643

AET-C 0002018 – AET-C 0007430

AET-C 0007475 – AET-C 0014719

AET-C 0014792 – AET-C 0014794

AET-C00103216 – AET-C00103221

Cooper AET 00482 – Cooper AET 00483

INGENIX-AETNA_PHCS 0001 – INGENIX-AETNA_PHCS 0072

McCoy/Aetna 001 – McCoy/Aetna 002

III. PRODUCED MATERIALS

A. Correspondence

Letter from Geoffrey M. Sigler to Barry Epstein and Barbra Gail Quackenbos, “Cooper v. Aetna – Meet and Confer Sessions On Claim Data Production” (Jul. 3, 2008).

Letter from Richard Doren to Barry Epstein and Barbra Gail Quackenbos, “Cooper v. Aetna – Meet and Confer Sessions On Claim Data Production” with CD Aetna 002 (Jun. 9, 2008).

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Exhibit 2

UNITED STATES DISTRICT COURT
DISTRICT OF NEW JERSEY

)
)
IN RE: AETNA UCR LITIGATION) MDL NO. 2020
) (No. 2:07-CV-3541)
)
)
)
)

RESPONSIVE EXPERT REPORT OF DR. ROBIN CANTOR

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Appendix: Additional Results

Attachment R-1: Cantor Testimony

Attachment R-2: Materials Considered

I. Qualifications

1. My name is Robin Cantor. I am a Principal in the Alexandria, VA office of Exponent, Inc. I specialize in applied economics, environmental and energy economics, statistics, and risk management. I have a B.S. in mathematics from Indiana University of Pennsylvania with a specialization in statistics and a Ph.D. in economics from Duke University with a specialization in econometrics.
2. I submitted an expert report in this matter (“Cantor Report”) on April 6, 2010. A more detailed discussion of my qualifications and curriculum vita are contained therein. My testimonial experience in the last four years is attached as Attachment R-1. My current billing rate for this engagement is \$570/hour for analysis and testimony. Other Exponent staff members have also worked at my direction on this matter and they have been billed at rates ranging from \$85 to \$335/hour.

II. Assignment

3. I have been engaged by Gibson, Dunn & Crutcher LLP (“Counsel”) on behalf of its clients, Aetna Health Inc. PA, Corp., Aetna Health Management, LLC, Aetna Life Insurance Company, Aetna Health And Life Insurance Company, Aetna Health Inc., Aetna Insurance Company of Connecticut, and Aetna, Inc. (collectively, “Aetna” or “Defendants”¹), to provide an expert opinion in the matters that have been consolidated as *In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation* (MDL No. 2020).
4. Since submitting the Cantor Report, I received and reviewed the reports submitted by Plaintiffs’ experts.² I have been asked to supplement my original report and opinions as necessary to address the analyses and opinions contained in the reports from Plaintiffs’ experts.
5. I understand that this matter involves three sets of proposed class plaintiffs: (a) health plan members (i.e., individuals enrolled in health plans who received out-of-network (“ONET”) services); (b) medical providers (i.e., individuals who provided healthcare services to members); and (c) associations (i.e., groups that represent providers) (collectively, “Plaintiffs”).³ I understand also that plaintiff Weintraub further brings this action against UnitedHealth Group, Inc. (“UHG”) and Ingenix, Inc. (“Ingenix”).
6. In these matters, Plaintiffs allege that (a) due to an inherent conflict of interest, the Ingenix Prevailing Healthcare Charges System (“PHCS”) Database (the “Ingenix Database”) of provider charge information was flawed in its construction and compilation, leading to systematically lower distributions of charges as reported in the Ingenix Database; and (b) when Aetna used these allegedly flawed data to determine the

¹ In this report, “Defendants” refers only to the referenced Aetna entities and no other parties.

² See Expert Report of Stephen Foreman, PhD, JD, MPA, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the “Foreman Report”); Expert Witness Report of Gordon Rausser, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the “Rausser Report”); and Plaintiffs’ Expert Report dated April 6, 2010 of Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the “Siskin Aetna Report”) (collectively, the “Plaintiffs’ Expert Reports”).

³ See Joint Consolidated Amended Class Action Complaint and Demand for Jury Trial, In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation (MDL No. 2020 filed Jul. 1, 2009) (the “Complaint”) at ¶ 1.

usual, customary and reasonable rates (“UCR”)⁴ for determining reimbursement of ONET services, Aetna’s reimbursement rates for ONET services were lower than they would have been if Aetna had used a data source that did not suffer from the alleged flaws in the Ingenix Database. According to the Complaint, Aetna and other alleged co-conspirators “knowingly created, manipulated and used flawed data to set artificially low reimbursement rates for ONET.”⁵ The Plaintiffs are asserting these claims on behalf of purported classes of members and providers throughout the United States who received or provided any type of medical services on an ONET basis where Aetna allowed less than the provider’s billed charge in determining benefits.⁶

7. The scope of my original assignment was (a) to use standard statistical and economic methods to investigate whether there is evidence that the alleged fundamental flaws in the data sampling and compilation methods resulted in a systematic downward skewing of the Ingenix Database values; (b) to investigate whether there is evidence that use of the Ingenix Database values would systematically lead to under reimbursement on an across-the-board basis for all (or nearly all) members of the purported classes; and (c) to consider whether my findings demonstrate statistical or economic conditions that would result in fundamental conflicts among members of the proposed classes, fatal flaws in the methodology to prove class-wide impact, or both.
8. In this responsive report, I consider Plaintiffs’ Expert Reports and conduct additional analysis to investigate whether the findings and opinions contained therein alter or refute my original results and conclusions.
9. My opinions are based on my understanding of the information available to me as of the date of this report and my experience and training as an economist. In the event that additional relevant materials are made available to me, I will consider such information as necessary. I reserve the right to supplement this report based upon any additional work that I might conduct or supervise from my review of such materials.
10. In conducting my analysis for this responsive report, I collected and reviewed publicly available information, case pleadings, and certain documents and depositions produced in discovery for this matter. The materials I considered for my analyses are listed in the footnotes of this report and in Attachment R-2.

III. Summary of Findings and Opinions

11. In this matter, Plaintiffs allege that Aetna’s behavior related to data contribution and use of the Ingenix Database has been infected by conflicts of interest and conspiratorial conduct. Plaintiffs claim that such behavior has resulted in lowering the upper percentile values of the Ingenix Database that Aetna uses to calculate UCR rates for ONET services. As a result, Plaintiffs allege that members of the proposed classes have been under reimbursed. My analysis of Plaintiffs’ Expert Reports primarily addresses their

⁴ Aetna defines the reasonable and customary amount as “the prevailing charge for the service or supply in the geographic area where it is furnished.” See AET-C00103216. As described in more detail in paragraph 25, the terms of Aetna’s plans vary, and reimbursement for ONET claims may be based on UCR, reasonable, usual and customary, or prevailing charge plan language.

⁵ See, e.g., Complaint at ¶ 5.

⁶ See, e.g., Complaint at ¶¶ 549 and 562.

opinions regarding whether the alleged common impact follows from the alleged conduct, and whether damages are subject to class-wide proof.

12. Plaintiffs' experts opine that members of the proposed classes have suffered class-wide impact because Aetna relies upon artificially low Ingenix Database upper percentile values to calculate UCRs.⁷ Not one of the three experts, however, has investigated, much less confirmed, this conclusion through independent empirical investigation for the instant matter. In the Cantor Report, I identified a number of sources of industry data that are readily available for such analysis and apparently are free of the alleged unlawful conduct. Using these benchmark databases, my analysis showed that Ingenix Database values are frequently greater than the benchmark values and that comparison with the benchmark databases fail to support an allegation that Ingenix Database values are lower than the benchmarks across the board. Based on my analysis of the readily available databases, I concluded that Plaintiffs cannot show common impact for the purported classes by reference to existing commercial and government benchmarks all of which apparently are not infected by the alleged conflict of interest or conspiracy allegations.
13. Although some of these data sources are also known to or have been used by Plaintiffs' experts,⁸ apparently not one of them chose to use these commercial or government databases to test their fundamental assumption that the Ingenix values are downwardly biased on a class-wide basis. Not one of Plaintiffs' experts conducted an independent empirical analysis of this claim. Moreover, Plaintiffs' experts have not rejected the available benchmarks based on any proper analysis of their validity in the instant matter; instead they have referenced the small market share of competitor products as if that factor was a certain indication of their reliability as billed charge databases. It is inexplicable given the prior experience of Plaintiffs' experts that all three of them failed to provide a proper investigation of the application of the available benchmarks in the instant matter.
14. Instead, two of Plaintiffs' experts defer to the recent study by the New York Attorney General of the Ingenix Database values⁹ as a foundation for their opinions about under reimbursement. Although these experts cite the NYAG Report in the context of under reimbursement,¹⁰ neither has provided any detailed analysis of the assumptions and/or findings in the NYAG Report in the expert reports or expert discovery materials that I have received. Nor have Plaintiffs' experts reported any analysis to generalize the conclusions asserted in the NYAG Report beyond the six CPT codes and two counties for which the NYAG published results. Plaintiffs' experts apparently have accepted the findings of the NYAG Report without any proper analysis of its data, methodology, or generality. Moreover, the NYAG Report cannot be the panacea for the common impact burden that Plaintiffs bear. The NYAG Report clearly indicates that in one of the only two counties for which results are reported, there are CPTs with either no or an immaterial downward bias.

⁷ See Foreman Report at ¶¶ 10 and 140; Rausser Report at ¶ 14; and Siskin Aetna Report at p. 6.

⁸ See Foreman Report at ¶¶ 41 and 44; and Siskin Aetna Report at p. 34.

⁹ See State of New York, Office of the Attorney General, "Health Care Report: The Consumer Reimbursement System is Code Blue," (Jan. 4, 2009) (the "NYAG Report").

¹⁰ See Foreman Report at ¶ 50; and Rausser Report at ¶¶ 60-61.

15. In the Cantor Report, I explained that my investigation of the Ingenix Database values follows the same methodology for investigating under reimbursement as the one described by the NYAG Report. I also found, however, fundamentally different results from the conclusions stated in the NYAG Report. When I apply this methodology beyond the two counties for which data were published by the NYAG Report, my analysis fails to support expanding the conclusions stated in the NYAG Report to the class as a whole. I have expanded that analysis for the instant report by examining a broader list of subject services as suggested by Dr. Foreman, one of Plaintiffs' experts.¹¹ When Ingenix Database values are compared to the available benchmarks in the subject counties addressed by the NYAG Report for the expanded list of 10 services to address high-cost CPTs, the results fail to support that there are consistently lower values for any of the five subject counties—including Erie County. Moreover, across New York State, my new results corroborate my earlier findings indicating that Ingenix Database values tend to exceed the benchmark values for the subject services.
16. The NYAG Report is consistent with my findings indicating no current benchmark which can be used to show a downward bias in the Ingenix Database values for all (or nearly all) relevant CPT and geographic area combinations. Importantly, I show that the percent differences for many CPT and geographic area combinations vary in direction across benchmarks. Thus, selection of the benchmark is a likely source of antagonistic interests among members of the proposed classes. None of Plaintiffs' experts have addressed this fundamental issue in their reports.
17. Plaintiffs' experts rather have focused a substantial portion of their criticisms of the Ingenix Database on the alleged methodology to estimate derived values.¹² I showed in the Cantor Report that derived values account for less than 0.5 percent of the total claim count in the medical and surgical modules of the Ingenix Database. Thus, any conclusions by Plaintiffs' experts about the derived values should not be extended to the Ingenix Database values more generally without substantial further analysis. To address the concerns of Plaintiffs' experts about the derived values, I have expanded my benchmark analysis to test whether they are systematically and pervasively low compared to the benchmark values. In stark contrast to Plaintiffs' claims and their experts' contentions, my empirical analysis shows that derived values at least for the medical and surgical procedures in the Ingenix Database exceed the benchmark values by a wide margin. Based on this analysis, I conclude that Plaintiffs' experts' concerns about derived values are completely misplaced.
18. Instead of using readily available fee data to conduct a direct benchmark analysis, Plaintiffs' experts have used hypothetical simulations to illustrate the impact of various alleged scrubbing rules on upper percentile values.¹³ Plaintiffs' experts have not provided a foundation for the generality or robustness of these simulations. Even if the

¹¹ See Foreman Report at ¶ 38. Neither the NYAG Report nor Dr. Foreman provide a list of the “ten common procedures and ten expensive procedures.” As a result, in my analysis below I expanded my investigation of the NYAG Report conclusions by estimating what the list of 10 high-cost procedures might have been using data from the 2007 Ingenix Database.

¹² See Foreman Report at ¶¶ 113-121; and Siskin Aetna Report at pp. 28-33. Derived value distributions have fewer than nine occurrences for a given procedure in a given geozip.

¹³ See, e.g., Foreman Report at ¶¶ 99-103 and 119-120; and Siskin Aetna Report at pp. 22-23, 27-28, and 32-33.

consequences for the upper percentile values suggested by the simulations of Plaintiffs' experts are true for some data inputs or some processing practices used for constructing distributions in the Ingenix Database, none of Plaintiffs' experts have demonstrated the generality or significance of these consequences. They have not provided any analysis indicating the likely prevalence or even the existence of the alleged consequences in the actual data that cover tens of millions of procedure by geographic area distributions over the 2001 to 2010 time period. Plaintiffs' experts have simply asserted that ultimately they can provide such a demonstration. In contrast, simple illustrative modeling with empirical data fails to demonstrate the patterns or impacts that Plaintiffs' experts argue are caused by the alleged flawed methodology for data contribution and processing.

19. In summary, Plaintiffs' experts have eschewed straightforward empirical testing of whether the alleged conduct has led to a common impact that can be demonstrated on a class-wide basis for this matter. Given they have ignored readily available benchmark data and standard methods to conduct a science-based investigation of this issue, their hypothetical arguments and hand-picked simulations lack credibility as a matter of statistics and economics.

IV. Bases for Opinions

A. *Plaintiffs' Experts Provide No Class-Wide Proof of Common Impact from the Alleged Conduct*

1. Siskin Report

20. In his expert report for the instant matter, Dr. Siskin reviews Ingenix's methodology to collect data from data contributors as well as the methodology Ingenix employs to analyze and publish these data.¹⁴ Dr. Siskin opines that because the dataset lacks factors such as patient characteristics, provider qualifications, or medical market area, the "Ingenix Databases do not allow one to compute a distribution of charges which are sufficiently similar that one can reasonably assess which charges are reasonable and which are 'too high.'"¹⁵
21. As I explained in the Cantor Report, a critical assumption in the instant matter and the prior investigations is that separating the data of the existing distributions to produce "similarly situated" conditions will indicate higher UCR values for the purported classes. It cannot be presumed, however, that separation of the existing distributions would result in higher upper percentile values for all or nearly all Plaintiffs. In fact, given the degree of aggregation described by Plaintiffs and the large number of contributors to the Ingenix Database, it is highly likely that many distributions would have lower values for the upper percentiles if the charges were separated as suggested by Plaintiffs. Consequently, in Plaintiffs' proposed "but-for" world, many separated distributions would imply lower UCR rates for substantial proportions of members of the purported classes. The interests of proposed class members in the upper distributions are directly and fundamentally in conflict with the interests of proposed class members in the lower distributions.

¹⁴ See Siskin Aetna Report at pp. 10-34.

¹⁵ See Siskin Aetna Report at p. 5. I note that the issue of differences in provider qualifications also is raised by Dr. Foreman in his expert report at ¶ 82.

22. An additional problem with Dr. Siskin's concern about missing factors is that he presents no foundation for the generality of the concern. Dr. Siskin reports no analysis to indicate which and how many distributions would vary materially from current versions if factors such as patient characteristics or provider qualifications were considered. It is not clear, for example, how a factor such as physician qualifications—which might not be available consistently from existing common data sources—will be addressed. In addition, Dr. Siskin provides no methodology to identify reliably the subject distributions that might be affected by the missing factors. The Ingenix Database contains about 7.5 million CPT by geozip distributions in the medical and surgical modules for 2006 alone. Individual reviews of each distribution for the necessary “missing” data and evidence of an influence from the alleged missing factors for all years in the Class Period is a daunting—if not impossible—task.
23. Regarding the allegations of flawed processing methodology, Dr. Siskin criticizes the way Ingenix addresses charge data containing modifiers. In so doing, he argues that “[t]his procedure, by definition, means that this database cannot be used to assess the reasonableness of any medical charges submitted to an insurer with these modifiers.”¹⁶ As another example, Dr. Siskin criticizes the methodology that Ingenix uses to standardize data values among different CPT codes. Similarly, he criticizes the high and low formulas used to eliminate outlier data. He argues that these rules result in values that are “not adjusted for the differences in the spread of charges within each CPT code (measured statistically by standard deviation from the mean).”¹⁷ He concludes that the consequence of these methods is to eliminate valid high charges from the resulting billed value distributions.¹⁸
24. Dr. Siskin uses hypothetical examples to illustrate the impact of these alleged scrubbing rules on upper percentile values.¹⁹ He also references the single actual case of Jill Faddis, a CIGNA subscriber, “relating to her husband’s R&C reimbursement for a dental procedure,”²⁰ reporting the resulting data from her survey.²¹ Remarkably, Dr. Siskin claims that “[t]he same phenomenon illustrated by Ms. Faddis’s survey of periodontists and dentists occurs for *all* types of procedures in *all* geographic areas.” (emphasis added)²² He does so with no reported testing of the generality or broader validity of the Faddis example and no proffered methodology to investigate this fundamental issue. Rather, Dr. Siskin concludes that this single case “confirms [his] opinion”²³ that Ingenix understates upper percentile values.
25. Dr. Siskin fails to report a methodology not only for testing the Faddis “phenomenon” but also for reliably proving any of his proffered hypotheses on an empirical basis. A review of the previously submitted and related reports of Dr. Siskin indicates that he has been repeating his arguments about the Ingenix Database since at least 2004 and still he

¹⁶ See Siskin Aetna Report at p. 21.

¹⁷ See Siskin Aetna Report at p. 22.

¹⁸ *Ibid.*

¹⁹ See, e.g., Siskin Aetna Report at pp. 22-23 and 27.

²⁰ See Siskin Aetna Report at p. 24.

²¹ See Siskin Aetna Report at pp. 24-26.

²² See Siskin Aetna Report at p. 26.

²³ *Ibid.*

has not attempted to test the reliability of his claims.²⁴ In all of these years and in at least three reports, Dr. Siskin has not conducted a proper statistical investigation of whether there is a systematic downward bias in the Ingenix Database values, much less whether a common impact from this bias can be demonstrated on a class-wide basis.

26. Dr. Siskin further opines that the methodology used for creating derived data for CPT codes with fewer than nine claims does not use proper standardization methods and therefore biases downward the upper percentile values.²⁵ I showed in the Cantor Report that derived values account for less than 0.5 percent of the total claim count in the medical and surgical categories of the Ingenix Database.²⁶ Thus, any conclusions by Plaintiffs' experts about the derived values should not be extended to the Ingenix Database values more generally without substantial further analysis, which neither Dr. Siskin nor any other Plaintiff expert has reported. Notwithstanding the limited proportion of derived claims in overall claim count and estimated revenues, I conduct an analysis below of the derived values to address Plaintiffs' expert's concerns. Benchmarking and the same standard matched-pair analysis of the Cantor Report fails to support Dr. Siskin's opinion that Ingenix Database values are downwardly biased even when restricted to derived claims only.

2. Foreman Report

27. Dr. Foreman was retained by the Plaintiffs to:

[R]ender a report on the ability to demonstrate through competent econometric evidence that: (a) Defendants' conduct caused [...] class-wide impact and injury; and (b) such impact and injury may be calculated and determined on a class-wide basis.²⁷

28. Dr. Foreman has prior knowledge about commercial and government databases used to examine physician fees and ONET health insurance payment issues. When discussing his qualifications in his expert report, Foreman notes that he served as an expert to the New York Attorney General ("NYAG") for out-of-network health insurance payment issues²⁸ and evaluated a proposed physician fee schedule for automobile accident injuries developed by Ingenix consultants on behalf of the Medical Society of New Jersey.²⁹ For his NYAG assignment, Dr. Foreman generated percentile distributions using Medicare claims data "in the form of limited data set five percent carrier files for 2006"³⁰ ("Medicare 5% Sample"). In the proceedings for a decision by the Court of New Jersey, Appellate Division made in 2009, the Alliance for Quality Healthcare submitted a report by Dr. Foreman as a comment.³¹ In his 2006 report for that matter, Dr. Foreman used

²⁴ See Expert Report of Bernard R. Siskin, Ph.D., Wachtel v. Health Net, McCoy v. Health Net (Mar. 31, 2004); Supplemental Expert Report of Bernard R. Siskin, Ph.D., Wachtel v. Health Net, McCoy v. Health Net (Jun. 15, 2006); and Siskin Aetna Report at p. 4.

²⁵ See Siskin Aetna Report at p. 30-32. I note that Dr. Foreman also raises the issue of derived data (what he calls "relative value imputation") in his report at ¶¶ 113-121.

²⁶ See Cantor Report at ¶ 62.

²⁷ See Foreman Report at ¶ 1.

²⁸ See Foreman Report at ¶¶ 5 and 14.

²⁹ See Foreman Report at ¶ 15.

³⁰ See Foreman Report at ¶¶ 41 and 44.

³¹ See In Re Adoption of N.J.A.C. 11:3-29 by the State of New Jersey, Department of Banking and Insurance, No.

Physicians' Fee Reference ("PFR") data provided by Wasserman Medical Publishers, Ltd. as a proposed fee source for evaluating arbitration award decisions and the proposed fee schedule.³²

29. Importantly, in his report on the New Jersey PIP Medical Fee Schedules, Dr. Foreman stated:

In order to evaluate these codes we searched for a source of data that would be comparable, accessible, easily used, *unbiased*, and would permit an analysis using statutory standards. The data that come closest and is *recognized by coding experts as the nearest available (accessible) substitute for "usual, customary and reasonable" fee comparisons* is the Physicians' Fee Reference (PFR) provided by Wasserman Medical Publishers, Ltd. Built. (emphasis added)³³

....

[T]he PFR is available to all, inexpensive to acquire, totally transparent, *unbiased*, and geographically sensitive because it is available at the ZIP code level. A fee schedule based on the PFR would be easy to build and maintain (particularly because the PFR is updated annually). Such a system would provide certainty of results over the entire range of CPT codes. (emphasis added)³⁴

A-0344-07T3 (N.J. Super. Ct. App. Div. filed Aug. 10, 2009) at p. 16.

³² See Foreman, S., "An Analysis of the Proposed New Jersey PIP Medical Fee Schedules Physician Fees and Ambulatory Surgery Center Facility Fees," (Dec. 4, 2006) (the "Foreman NJ Report") at pp. 5-7.

³³ See Foreman NJ Report at pp. 5-6.

³⁴ See Foreman NJ Report at p. 10. I note that the geographic adjustment factor ("GAF") data for PFR is available at the geozip and zipcode levels. I tested whether the zipcode GAFs within a geozip differed substantially from the relevant geozip GAF by having Exponent staff extract 10 geozips at random from the 2006 PFR. Exponent then queried the PFR software to extract the more than 400 zipcode GAFs that mapped into the 10 geozips. The zipcode and relevant geozip GAFs were compared and showed no percent differences exceeding plus or minus 0.3 percent. Based on this review, I have continued to use the geozip GAF data for PFR in my analyses.

30. In spite of his apparent endorsement and comfort with PFR as a benchmark for fee analysis, Dr. Foreman does not use it or reference it in his analysis for the instant matter. In his expert report for the instant matter, Dr. Foreman cites internal Ingenix planning documents and the 2009 U.S. Senate Committee on Commerce, Science and Transportation Report to Chairman Rockefeller (the “Rockefeller Report”) to support his contention that there are “very few other firms that supply percentile software.”³⁵ He also references an Ingenix document “stating [it] owns 80% of the benchmarking market.”³⁶
31. The magnitude of the Ingenix share of the “benchmarking market,” however, does not diminish the existence or apparently, based on Dr. Foreman’s previous remarks about PFR, the quality of other products. The Senate Committee statements about competitor products and measures of Ingenix’s market share are not valid scientific reasons for ignoring available data and benchmarks to address the issue of common impact. Plaintiffs’ experts have not rejected the benchmarks based on any proper analysis of their validity in the instant matter; instead they have referenced the small market share of competitor products as if that factor was a certain indication of their reliability as billed charge databases. I provided information about the ease of locating and obtaining these products in the Cantor Report. I also provided information indicating that these products are known to and used by healthcare researchers in their analytical work, apparently with little controversy about their external validity. A simple internet search of terms such as “benchmarking healthcare fees” easily locates these products. It is inexplicable that given his prior and recent experience with the application of PFR for fee benchmarking, Dr. Foreman fails to investigate its applicability for his assignment in the instant matter.

³⁵ See Foreman Report at ¶ 68.

³⁶ See Foreman Report at note 15. The document that Dr. Foreman references mentions Captiva which was a provider of PMIC data. The PMIC 2006 Manual states:

Medical Fees in the United States 2006 is the result of a publishing collaboration between EMC Captiva and Practice Management Information Corporation.

EMC CAPTIVA

EMC Captiva is a leading developer of reimbursement products for the health care industry. Perhaps best known for its Codelink, Claims Editor and ICD-9-CM software programs, the firm also markets numerous fee, coding and regulatory database products. Captiva/Context products are used by thousands of health care organizations, from solo physician practices to Fortune 500 companies.

PRACTICE MANAGEMENT INFORMATION CORPORATION (PMIC)

PMIC is the nation’s leading independent publisher and distributor of coding, reimbursement and practice management books and software. The company is known for its innovative, high quality products and excellent customer service. Over 100,000 physicians, hospitals, insurance carriers, and other health care professionals regularly choose PMIC as their complete medical book resource. The company was listed twice in the Inc. Magazine list of the 500 fastest growing privately held companies in America. PMIC maintains its corporate office in Los Angeles and its sales office in the metropolitan Chicago area. See Practice Management Information Corporation. 2006. *Medical Fees in the United States 2006*. Los Angeles, CA: Practice Management Information Corporation at p. v.

32. Dr. Foreman does suggest in his expert report that Medicare billed charge claims data and Medicaid claims data could be used in estimating damages. Dr. Foreman states:

[T]here is no reason to believe that Medicare billed charges or Medicaid billed charges differ systematically from the billed charges made to private commercial health insurers or, for that matter, among private commercial health insurers. However, it would be tractable to test this and to provide adjustments for any systematic bias that might be found.³⁷

33. Rather than simply asserting its potential usefulness, I use the Medicare Physician/Supplier Procedure Summary (“Medicare PSPS”) data in the Cantor Report to investigate whether Ingenix Database values are downwardly biased. My results showed that Ingenix Database values tend to exceed Medicare PSPS values and did so for more than half of the comparisons in the nationwide analysis.³⁸

34. Like Dr. Siskin, Dr. Foreman’s core analytical work relies on hypothetical data and simulation. He references the Siskin Aetna Report to criticize Ingenix’s methodology for dealing with outliers (what Dr. Foreman calls the “high-low screen”)³⁹ and concludes that this screen “provides a decidedly downward bias to the Ingenix rate tables.”⁴⁰ Dr. Foreman suggests that Ingenix’s use of prior period data to set the “high-low screen” will create a “regression to the median” for the upper percentile data. As a result, he expects upper percentile values to fall over time. Dr. Foreman then uses an “illustrative simulation” for CPT 99213 to show how his argument would work.⁴¹ Like Dr. Siskin, Dr. Foreman also fails to provide an analysis or methodology to demonstrate that his alleged impact exists at all in the actual billed charge distributions of the Ingenix Database or that his alleged impact could be generalized across all CPT codes and all geographic areas and all time periods that are in the purported class.

35. A simple illustrative model based on actual data for the CPT 99213, however, can be used to show that there are problems with Dr. Foreman’s theory. Using a regression based on the Ingenix empirical data and data from PFR for CPT 99213, I test whether Ingenix Database upper percentile values declined between 2006 and 2007, controlling for other market and geographic factors. The dependent variable is Ingenix’s value for the 75th or 90th percentiles and the independent variables are the “matched” PFR values for the 75th or 90th percentiles (to control for other market and geographical factors) and an indicator variable equal to one if the observation is from the year 2007, and zero if the

³⁷ See Foreman Report at note 48. I note that none of Plaintiffs’ experts have reported any analysis regarding the external validity of the Medicare or other commercial database values as benchmarks for UCRs. Should Plaintiffs’ experts eventually acknowledge that there are industry sources of billed fees and additionally perform investigations of their external validity, I reserve the right to consider such analyses in the context of my findings and opinions.

³⁸ I note that I was not given permission by the Centers for Medicare and Medicaid Services (“CMS”) to use the Medicare 5% Sample to conduct an analysis of values other than the average billed amount from the Medicare PSPS database. Should such data become available in this litigation, I reserve the right to consider it in the context of my findings and opinions.

³⁹ See Foreman Report at ¶ 85.

⁴⁰ See Foreman Report at ¶ 95.

⁴¹ See Foreman Report at ¶¶ 99-103 and App. C. Regarding Dr. Foreman’s analysis and results in his Exhibit C, I have concerns about how he standardized the procedures that he pooled for the analysis and whether there are mathematical errors. I also have concerns that his application of the “high-low screen” fails to match his written description and the description found in Dr. Siskin’s report. My work on this issue continues.

observation is from the year 2006. In this simple illustrative model, the 2007 indicator measures whether, on average, Ingenix Database upper percentile values have increased, decreased, or stayed the same between 2006 and 2007. The results shown in Table R1 indicate that the coefficient for the 2007 time indicator is positive and marginally statistically significant (with a p-value of approximately 0.11), suggesting that upper percentile levels increased between 2006 and 2007, all else the same. These results fail to support Dr. Foreman's theory. Notably, the simple model also shows a strong relationship between the Ingenix value and the PFR value. The coefficient is positive and highly statistically significant (with a p-value <.0001). The 95% confidence interval for the coefficient includes values greater than one. This illustrative result fails to support Plaintiffs' general theory that when compared to an unbiased standard,⁴² the upper percentile values in the Ingenix Database are systematically low.

Table R1: Regression Results for Illustrative Analysis of CPT 99213

Linear Regression

Number of Observations	=	3590
F Value	=	1152.57
Prob. > F	=	<0.0001
R-Squared	=	0.3912
Adjusted R-Squared	=	0.3909

	Coefficient	Std. Error	t-value	Pr > t 	95 % Confidence Interval
Intercept	4.28839	1.86280	2.30	0.0214	0.63615 7.94064
Time	0.72133	0.44953	1.60	0.1087	-0.16003 1.60269
PFR_percentile	0.97306	0.02085	46.66	<.0001	0.93217 1.01395

Notes:

1. *Ingenix Value (percentile p, geozip g, time t) = Intercept + 2007 yr indicator + PFR Value (percentile p, geozip g, time t).*

36. In his discussion about Ingenix's use of the geozip to organize data geographically, Dr. Foreman argues that Ingenix faces "small numbers issues."⁴³ He suggests that the practice of reporting billed charge percentiles for geozip/CPT combinations with ten or more billed charge claims is insufficient for statistical confidence. I have expanded my analysis in the Cantor Report with a sensitivity study of matched pairs that depend on Ingenix Database values derived from at least 80 claims to test whether Dr. Foreman's concern about small numbers might affect my results about percent differences. Table 2 shows that restricting my analysis to combinations with 80 or more billed charge claims does not disturb the conclusions from the Cantor Report.⁴⁴ Percent differences between Ingenix and benchmark values still tend to be small or positive. In fact, the simple averages no longer indicate *any* results more negative than minus 5 percent. Moreover, a substantial proportion of the matched-pair results continue to be equal to zero or positive which is contrary to Plaintiffs' theory of a common adverse impact from the alleged conduct.

⁴² Here I refer to Dr. Foreman's assessment that PFR is unbiased, as indicated in the Foreman NJ Report.

⁴³ See Foreman Report at ¶¶ 130-134.

⁴⁴ Additional tables for the claim- and revenue-weighted results are included in the Appendix.

Table R2: Results of Simple Average of Matches, with Claims Restrictions Suggested by Dr. Foreman

Benchmark	2005 ⁷				2006			
	Average Percent Difference		Proportion of Matches ≥ 0		Average Percent Difference		Proportion of Matches ≥ 0	
	Cantor Report ⁸	≥ 80 Claims						
MAG – 80 ^{th1}	9.38%	7.11%	50%	48%	-1.70%	-4.57%	37%	33%
MAG – 90 ^{th2}	19.85%	18.25%	60%	60%	7.33%	5.05%	48%	46%
Medicare PSPS – all ³					12.86%	9.29%	57%	57%
Medicare PSPS – subset ^{3,4}					10.11%	7.86%	55%	56%
NDAS ⁵					-9.37%	-4.93%	31%	35%
PFR ⁶					-0.83%	-2.19%	42%	41%
PMIC – all ⁶	-3.09%	-2.29%	39%	40%	-0.87%	-0.13%	41%	42%
PMIC – subset ^{4,6}	2.41%	5.46%	46%	51%	4.88%	7.71%	48%	53%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.
8. See Cantor Report at tbl. 15.

37. In summary, Dr. Foreman provides a litany of alleged practices that he believes will cause the “but-for” Ingenix Database values to differ from the actual values and finally result in under reimbursement of Plaintiffs for their ONET claims.⁴⁵ Although Dr. Foreman proffers no direct class-wide proof of the alleged under reimbursement in his report, he does reference the NYAG Report as an example of such analysis.⁴⁶ From Dr. Foreman’s description of the NYAG, I understand that it addressed a larger number of procedures than reported in the published document and that I have already addressed in the Cantor Report. I have expanded my analysis of the NYAG conclusions to address the limited additional information that Dr. Foreman provides about the NYAG review of high-cost procedures. I report these results below. I note, however, that complete details about the NYAG Report and Dr. Foreman’s analytical work products for it have not been made available publicly and have not been produced in connection with Dr. Foreman’s report, and therefore are not available to me.

3. Rausser Report

38. Dr. Rausser was retained by the Plaintiffs to evaluate facts relevant to their antitrust claims brought under Section One of the Sherman Act which Plaintiffs contend are relevant to the upcoming motion for class certification.⁴⁷ One of the aspects that Dr. Rausser was asked to evaluate is the impact that would have been experienced by

⁴⁵ See Foreman Report at ¶¶ 136-137. In addition to the alleged practices discussed in the instant report, Dr. Foreman raises the issue of a “mean to median test” allegedly used by HIAA. Dr. Foreman acknowledges that there is no indication that Ingenix uses this test. See Foreman Report at ¶ 105.

⁴⁶ See Foreman Report at ¶¶ 37-52.

⁴⁷ See Rausser Report at ¶ 4.

class members assuming the allegations of the Complaint are true and whether this impact can be proved with shared evidence.⁴⁸

39. Dr. Rausser opines that impact can be proven with information common to the class using available data, but he does no independent analysis of available data to support his conclusion. Instead, Dr. Rausser's foundation for his opinion regarding class-wide proof includes references to the expert reports of Drs. Siskin and Foreman (neither of whom, as discussed above, provided empirical analysis as a foundation for this conclusion), the conclusions of the Rockefeller Report, the results of the NYAG Report, and the mere creation of the non-profit organization to which the PCHS/MDR database has been transferred.⁴⁹
40. The information Dr. Rausser cites on the issue of whether the alleged conduct results in a common impact also provides some glaring inconsistencies. For example, as part of his support for his opinion about common information, Dr. Rausser refers to the NYAG Report and reproduces the results for Erie County. In the Cantor report, I also have noted the across-the-board negative percent difference for Erie County for the six CPT codes published by the NYAG Report.⁵⁰ I further showed that the NYAG Report's results for Erie County as a whole for the six CPT codes are corroborated by the commercial benchmarks. Importantly, the NYAG Report also indicated the results for New York County (Manhattan). These results are reproduced in Table R3. The last two rows of the table indicate that either no or very small percent differences were found by the NYAG for two of the six CPTs in this county. Accordingly, based on the NYAG Report results, no significant adverse impact is indicated for one-third of the high-claim procedures reported for Manhattan. This result also highlights a more general problem with Plaintiffs' attempt to demonstrate classwide impact. In combination, my analysis and the NYAG Report indicate no current benchmark showing a downward bias in the Ingenix Database values for all (or nearly all) relevant CPT and geographic area combinations. In addition, the percent differences for many CPT and geographic area combinations vary in direction across benchmarks.⁵¹ Thus, selection of the benchmark is a source of antagonistic interests among members of the proposed classes. Neither Dr. Rausser nor any of Plaintiffs' other experts have addressed this issue.

⁴⁸ *Ibid.*

⁴⁹ Dr. Rausser states "the fact that prevailing rates can be accurately and fairly estimated is *borne out* by the efforts of the newly formed non-profit organization that has taken over the PCHS/MDR database" (emphasis added). See Rausser Report at ¶ 62. I cannot understand from Dr. Rausser's statement how the formation of this new organization *per se* will bear accurate and fair estimates on a class-wide basis.

⁵⁰ I note in this regard that the reported results are county-wide which could mask additional variation in the direction of the percent differences if the data were to be disaggregated to the geozip or other detailed level of geographic segmentation.

⁵¹ In Manhattan for example, the Cantor Report shows that members of the proposed classes having a 2007 claim related to CPT 99245 will benefit only if MAG 80th Percentile is the benchmark, but members with claims in the other five CPTs will benefit only if the NYAG Report Model Database is used as the benchmark.

Table R3: NYAG Report Results for Manhattan County

CPT	Values		Difference	
	"Model Database"	Ingenix Database	Dollars	Percent
99211	\$125	\$100	\$25	-20
99212	\$150	\$125	\$25	-17
99213	\$185	\$160	\$25	-14
99214	\$250	\$225	\$25	-10
99215	\$355	\$350	\$5	-1
99245	\$550	\$550	\$0	0

Source NYAG Report at tbl. 2.

41. Like Dr. Foreman, Dr. Rausser apparently is under the impression that “there were no alternative products available to insurers to use in setting reimbursements.”⁵² Dr. Rausser references the Foreman Report, an *American Health Association v. United Healthcare Corporation* filing, the testimony of participants in the Congressional Hearings, and the Rockefeller Report for this conclusion.⁵³ This examination of the market products is clearly inadequate. As part of his analysis regarding the composition of the benchmark data market and the existence of information common to the class, Dr. Rausser should have identified and considered the commercial and government products that I easily identified. At the very least, he should have considered whether the high Ingenix market share that he observes is the result of possible economic and technical factors such as reliability, coverage, ease of use, etc. that favor the Ingenix product relative to the competing products.

B. The NYAG Report Fails to Support Common Impact

42. In the Cantor Report, I examined the conclusions of the NYAG Report and tested whether they were robust to the three subject counties for which results were not reported and statewide. Importantly, I found that for the five subject counties and statewide, no allegation of a common downward bias could be supported by the percent differences between the Ingenix Database values and available commercial benchmarks for six subject high-claim-count CPTs.

43. Dr. Foreman has indicated in his report that the NYAG analysis also addressed high-cost CPTs, the results of which were not published in the NYAG Report. I have expanded my analysis of percent differences to 10 high-cost procedures.⁵⁴ Table R4 lists this set of subject CPTs.

⁵² See, e.g., Rausser Report at p. 10.

⁵³ See Rausser Report at notes 78-81.

⁵⁴ I understand Dr. Foreman has not produced a list of the procedures that he references in his report, so I have estimated his list by extracting the 10 procedures with the highest billed amounts in the 80th percentile of the 2007 Ingenix Database for New York State.

Table R4: Listing of Top 10 CPTs by Cost in the 2007 Ingenix Database

CPT	Description ¹	Charge ²
61518	Removal of brain lesion	\$65,000
61510	Removal of brain lesion	\$55,000
22554	Neck spine fusion	\$45,000
61793	Focus radiation beam	\$42,500
61682	Intracranial vessel surgery	\$38,202
61608	Resect/excise cranial lesion	\$37,500
19364	Breast reconstruction	\$37,500
61343	Incise skull (press relief)	\$36,000
61697	Brain aneurysm repr complx	\$34,381
47135	Transplantation of liver	\$30,001

Notes:

1. Description as contained in the Ingenix Database.
2. Maximum value at the 80th percentile.

44. The simple average results for the high-cost CPTs are shown in Table R5.⁵⁵ Not all subject CPTs were found in all counties. The results show variation in the direction of the percent differences and in many cases there are large positive percentages. Consistent with the methodology described in the Cantor Report, positive percentages indicate that the value of the Ingenix Database is greater than the benchmark, and therefore is contrary to Plaintiffs' theory of a common adverse impact from the alleged conduct. Perhaps due to their lower claim count, the results for the high-cost CPTs demonstrate greater variation than I found for the high-claim-count CPTs. Notably, again in contrast to the previous set of subject CPTs, some of the percent differences for Erie County are also positive and large suggesting that results for the high-claim-count comparisons cannot be generalized to high-cost procedures.

⁵⁵ Additional tables for the claim and revenue weighted results are presented in the Appendix.

Table R5: Simple Average Percent Differences of Matches by County for the Top 10 CPTs by Cost (Per the 80th Percentile of the 2007 Ingenix Database)

CPT*	MAG		Medicare PSPS		PFR		PMIC	
	80 th Percentile	90 th Percentile	Mean	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	
Albany								
22554	40%	40%	39%	10%	29%	12%	18%	
61510	-35%	-35%	-16%	-28%	-38%	-17%	-29%	
Erie								
22554	-18%	-10%	9%	-14%	-19%	-12%	-26%	
61510	3%	3%	22%	14%	-2%	32%	12%	
61518	-35%	-24%	25%	-28%	-28%	-19%	-20%	
61793	40%	40%	32%	20%	35%	36%	31%	
Monroe								
22554	-7%	33%	22%	-6%	20%	-1%	13%	
47135	1%	1%	-5%	73%	32%	148%	103%	
61510	-19%	2%	13%	-23%	-5%	-8%	12%	
61793	-6%	6%	2%	3%	0%	20%	1%	
New York								
19364	158%	194%	36%	115%	102%	70%	72%	
22554	145%	176%	329%	141%	152%	111%	98%	
47135	-20%	-3%	-14%	40%	29%	67%	66%	
61343	154%	154%	265%	210%	189%	212%	165%	
61510	56%	71%	1%	71%	62%	71%	59%	
61518	101%	149%	10%	115%	135%	105%	123%	
61608	174%	174%	97%	119%	143%	78%	102%	
61682	88%	88%		170%	122%	34%	2%	
61697	90%	90%	1%	169%	135%	114%	62%	
61793	148%	202%	8%	165%	190%	158%	143%	
Onondaga								
22554	-13%	-13%	13%	-8%	-22%	-6%	-29%	
61510	-16%	-16%	33%	-10%	-22%	4%	-12%	
61793	-3%	-3%	27%	6%	-9%	20%	-11%	

Notes:

* County-specific results were not available for every CPT in , as the Ingenix Database did not contain claims information for all CPTs in this listing within each county. This table presents all possible comparisons.

45. The statewide results also fail to support a theory of systematic downward bias in the Ingenix Database values for the subject high-cost claims. Table R6 shows that nearly all of the percent differences are positive, which indicates that the values in the Ingenix Database are greater than the benchmarks. Based on this analysis, there is no reason to believe that my opinions in the Cantor Report regarding the NYAG Report's conclusions would be disturbed by a consideration of high-cost CPTs.

Table R6: Simple Average Percent Differences of Matches Statewide for the Top 10 CPTs by Cost (Per the 80th Percentile of the 2007 Ingenix Database)

CPT	MAG		Medicare PSPS		PFR		PMIC	
	80 th Percentile	90 th Percentile	Mean	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	
19364	175%	207%	29%	135%	110%	85%	78%	
22554	86%	103%	124%	65%	78%	50%	44%	
47135	-5%	1%	-13%	58%	28%	106%	79%	
61343	138%	138%	232%	190%	170%	191%	147%	
61510	48%	68%	35%	55%	54%	58%	55%	
61518	150%	195%	22%	170%	177%	157%	162%	
61608	174%	174%	97%	119%	143%	78%	102%	
61682	88%	88%		170%	122%	34%	2%	
61697	75%	75%	16%	148%	116%	96%	48%	
61793	94%	122%	201%	106%	108%	103%	75%	

C. Derived Values Are In Fact Consistent With Readily Available Benchmarks

46. In their criticisms of the Ingenix Database, Plaintiffs' experts refer to alleged scrubbing rules to estimate the derived values. My analysis in the Cantor Report did not include an analysis of derived values because they account for so little of the claim count or estimated revenues in the medical and surgical data modules. I have expanded my analysis to investigate whether derived values are downwardly biased across the board when compared to the commercial and government benchmarks.

47. Table R7 summarizes the 2006 Ingenix Database files and indicates the relative magnitudes of data that fall into the derived category. As shown in rows 3 and 5, derived fee data are frequently encountered for any given CPT or CDT, but they apply to only a fraction of the billed claims and estimated revenues compared to the totals.

Table R7: Summary of Ingenix 2006 Files

Description	CPT(CDT)	CPT(CDT)-by-Geozip ¹	Claims	Revenue ²
All files, all system codes	13,470	10,389,637	1,172,968,725	\$114,116,340,449
Dental (CDT codes)	514	274,053	155,039,899	\$15,452,709,148
Derived fees only ³	465	103,311	154,578	\$65,763,343
Medical and Surgical	8,370	7,438,790	747,243,081	\$87,188,761,656
Derived fees only ³ , selected system types ⁴	8,274	6,111,484	1,910,384	\$2,836,338,223

Notes:

1. Based on 899 Geozips.
2. Revenue = [mean value of fees]*[claims].
3. "Derived fees" are those with record type of "31" and "32."
4. "Selected system types" include Medical, Surgical, Radiology total, and Pathology/Lab total.

48. Table R8 shows the matched pair coverage possible for the observations in the Ingenix Database using the derived fee data for the systems that I examined in the Cantor Report. As noted in that report, derived fee distributions account for a large share of the medical and surgical observations in the Ingenix Database. The high levels of coverage for matches with the benchmarks in the table below, however, still should be put in the

context of the low levels of coverage for the total claims in the Ingenix Database and total estimated revenues.⁵⁶ Dental fee matches using NDAS, however, are an exception to the rule because a large share of the observations is covered by empirical distributions.

Table R8: Derived Matched-Pair Coverage of Ingenix Observations

Benchmark	CPT(CDT)-by-Geographic Unit ^{1,2}	Claims	Revenue
MAG	78%	0.2%	3.2%
Medicare PSPS – all	40%	0.2%	2.7%
Medicare PSPS – subset³	18%	0.1%	1.1%
NDAS	0.1%	0.003%	0.3%
PFR	79%	0.2%	3.2%
PMIC – all	79%	0.2%	3.2%
PMIC – subset³	37%	0.1%	1.3%

Notes:

1. “Geographic units” indicate the geographic level of matched-pair comparison; i.e., geozip or 5-digit ZIP code. The geographic unit for all benchmarks except for MAG is at the geozip level; MAG is at the 5-digit ZIP code level.
2. The percentage of unique CPT-geographic units.
3. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips. For example, unless otherwise noted, “PMIC” refers to the complete database and “PMIC – subset” refers to the 30 CMS regions.

a. Analysis excludes records for which all percentile values equaled zero or records where a lower percentile value exceeded a higher percentile value (e.g., 75th percentile value exceeded 80th percentile value).

49. Applying the same methodology of the Cantor Report, Table R9 shows the derived fee results from the matched-pair analysis with the commercial and government benchmarks. Only the comparison with NDAS in 2006 shows a negative percent difference. Otherwise, all other results are positive. As in the methodology described in the Cantor Report, positive differences indicate that the values reported in the Ingenix Database are greater than the benchmark, and are therefore contrary to Plaintiffs’ theory of a common adverse impact from the alleged conduct. All medical and surgical comparisons show percent differences that are zero or positive for a high proportion of the matches. For example, the PFR result in row 6 shows that 58.2 percent of the pairs indicate results that are contrary to Plaintiffs’ theory of downward bias.

50. Although the dental fee comparison with NDAS indicates a substantial negative percent difference, results are zero or positive for nearly 14 percent of the matches. The additional results in the Appendix show that the average percent difference is reduced when averages are weighted by claim and revenues factors.

⁵⁶ In examining the derived data, Exponent staff observed that there are distributions with uniformly zero or illogical values for the percentiles. These distributions were removed from the matched pairs and this restriction is reflected in the coverage measures in Table. This issue had little effect on the medical and surgical data.

Table R9: Results of Simple Average of Matches for Derived Fees

Benchmark	2005 ⁷			2006		
	No. of Matched Pairs	Average Percent Difference	Proportion of Matches ≥ 0	No. of Matched Pairs	Average Percent Difference	Proportion of Matches ≥ 0
MAG – 80 ^{th1}	8,885,179	39.3%	64.8%	9,082,103	105.0%	58.0%
MAG – 90 ^{th2}	8,885,179	68.4%	74.8%	9,082,103	145.2%	69.1%
Medicare PSPS – all ³				3,186,362	109.8%	58.1%
Medicare PSPS – subset ^{3,4}				1,364,848	74.2%	56.5%
NDAS ⁵				5,459	-28.4%	13.8%
PFR ⁶				5,888,350	23.8%	58.2%
PMIC – all ⁶	6,462,096	24.8%	55.0%	6,561,262	27.4%	55.1%
PMIC – subset ^{4,6}	2,561,497	31.9%	58.6%	2,738,118	34.9%	58.8%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.

a. Analysis excludes records for which all percentile values equaled zero or records where a lower percentile value exceeded a higher percentile value (e.g., 75th percentile value exceeded 80th percentile value).

51. The derived fee dental result is actually based on relatively small number of matched pairs that represent a tiny fraction of the dental claims and revenues. The obtained result affects only 0.01 percent of the dental claims in 2006 as shown in Table R10. In the entire set of Ingenix data available to me, derived dental data is always a tiny fraction of the total claims.

Table R10: Summary of Dental Empirical and Derived Values

Year	Claims					
	Total		Empirical		Derived	
	No.	No.	% Total	No.	% Total	
2002	94,824,861	94,717,001	99.89%	107,860	0.11%	
2003	75,589,975	75,474,006	99.85%	115,969	0.15%	
2004	95,133,112	95,013,442	99.87%	119,670	0.13%	
2005	118,473,011	118,343,063	99.89%	129,948	0.11%	
2006	154,906,009	154,885,321	99.99%	20,688	0.01%	
2007	150,529,954	150,508,570	99.99%	21,384	0.01%	

Notes:

a. Analysis excludes records for which all percentile values equaled zero or records where a lower percentile value exceeded a higher percentile value (e.g., 75th percentile value exceeded 80th percentile value).

52. This analysis of derived values fails to support the concerns of Plaintiffs’ experts regarding a purported downward bias from the methods to construct the distributions. These results suggest that Plaintiffs’ experts have expended a lot of effort to speculate about the impacts of the alleged conduct on a non-issue.

V. Conclusion

53. Plaintiffs' experts have provided a set of alleged data contribution and processing practices that they claim adversely affect upper percentile values in the Ingenix Database. They have not provided, however, the analysis that links these alleged practices to the actual Ingenix distributions and demonstrates that the adverse impacts will be found in all or nearly all of the distributions relevant to members of the purported classes. They have not provided proper analysis or methodology that demonstrates that a reliable approach to proving common impact on a class-wide basis exists and can be implemented in the instant matter. Plaintiffs' experts proffer hypothetical examples of their alleged impacts but fail to provide the necessary analysis or methodology to understand how and when these impacts will be found in the Ingenix Database distribution. The Ingenix Database contains millions of billed-charge distributions in each year and Plaintiffs' experts have not addressed how they will identify and distinguish distributions with affected data.
54. Standard testing with actual data and commercial and government benchmarks fails to support Plaintiffs' experts' conclusions about the consequences of the alleged flawed data contribution and processing methodology.
55. Plaintiff's experts cannot defer to the NYAG Report as an example of results showing common impact. The reported results in that study fail to show common impact even for the two counties in New York and six CPT codes that the NYAG elected to present in the NYAG report. My analysis of high-cost procedures casts further doubt on the validity of the conclusions asserted in the NYAG Report for the instant matter.
56. Although derived values apparently captured the attention of Plaintiffs' experts, my analysis fails to support the conclusion that a common or even average downward bias can reliably be detected in these values when compared to the commercial and government benchmarks.
57. In sum, extensive testing of Plaintiffs' theories and the database consequences proffered by Plaintiffs' experts fails to support the allegation that Ingenix Database values—empirical or derived—are downwardly biased across the board, or even on average. Moreover, Plaintiffs' experts have not identified or demonstrated the existence of a benchmark that results in an adverse impact for all or nearly all of the Ingenix distributions. Alternatively, my analysis demonstrates that the percent difference results even for a single procedural and geographic example can vary across benchmarks. Members of the purported classes have antagonistic interests regarding the class-wide methodology to develop or select a benchmark since the direction of the percent differences—and therefore the member's injury—is sensitive to that choice.



Robin Cantor
May 1, 2010

APPENDIX: ADDITIONAL RESULTS

For analyses where results for simple averages of matched pairs are presented in the report, this appendix presents their respective claim-weighted and dollar-weighted results. For consistency, tables are numbered as in the report, with the addition of “B” for claim-weighted results or “C” for dollar-weighted results.

Table R2B: Results of Claim-weighted Average of Matches, with Claims Restrictions Suggested by Dr. Foreman

Benchmark	2005 ⁷		2006	
	Cantor Report ⁸	≥ 80 Claims	Cantor Report ⁸	≥ 80 Claims
MAG – 80 ^{th1}	4.44%	4.28%	-5.99%	-6.12%
MAG – 90 ^{th2}	15.19%	18.25%	3.79%	3.69%
Medicare PSPS – all ³			7.94%	7.82%
Medicare PSPS – subset ^{3,4}			7.78%	7.72%
NDAS ⁵			-2.13%	-2.03%
PFR ⁶			-2.57%	-2.62%
PMIC – all ⁶	-0.78%	-0.73%	0.84%	0.87%
PMIC – subset ^{4,6}	8.08%	8.21%	10.77%	10.90%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.
8. See Cantor Report at tbl. 16.

Table R2C: Results of Dollar-weighted Average of Matches, with Claims Restrictions Suggested by Dr. Foreman

Benchmark	2005 ⁷		2006	
	Cantor Report ⁸	≥ 80 Claims	Cantor Report ⁸	≥ 80 Claims
MAG – 80 ^{th1}	10.97%	9.84%	2.99%	1.28%
MAG – 90 ^{th2}	21.28%	20.25%	12.60%	11.00%
Medicare PSPS – all ³			14.78%	13.47%
Medicare PSPS – subset ^{3,4}			14.95%	14.28%
NDAS ⁵			1.67%	1.80%
PFR ⁶			8.06%	7.61%
PMIC – all ⁶	3.87%	3.44%	5.64%	4.93%
PMIC – subset ^{4,6}	12.43%	9.27%	15.27%	10.62%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.
8. See Cantor Report at tbl. 17.

Table R5B: Claim-weighted Average Percent Differences of Matches for the Top 10 CPTs by Cost (Per the 80th Percentile of the Ingenix Database) (2007)

CPT*	MAG		Medicare PSPS		PFR		PMIC	
	80 th Percentile	90 th Percentile	Mean	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	
Albany								
22554	40%	40%	39%	10%	29%	12%	18%	
61510	-35%	-35%	-16%	-28%	-38%	-17%	-29%	
Erie								
22554	-20%	-5%	15%	-14%	-13%	-12%	-21%	
61510	3%	3%	22%	14%	-2%	32%	12%	
61518	-35%	-24%	25%	-28%	-28%	-19%	-20%	
61793	40%	40%	32%	20%	35%	36%	31%	
Monroe								
22554	-7%	33%	22%	-6%	20%	-1%	13%	
47135	0%	0%	-5%	73%	32%	148%	103%	
61510	-19%	2%	13%	-23%	-5%	-8%	12%	
61793	-6%	6%	2%	3%	0%	20%	1%	
New York								
19364	158%	194%	36%	107%	95%	70%	72%	
22554	145%	176%	329%	133%	143%	111%	98%	
47135	-20%	-3%	-14%	35%	25%	67%	66%	
61343	154%	154%	265%	199%	178%	212%	165%	
61510	56%	71%	1%	65%	56%	71%	59%	
61518	101%	149%	10%	107%	127%	105%	123%	
61608	174%	174%	97%	111%	134%	78%	102%	
61682	88%	88%		160%	114%	34%	2%	
61697	90%	90%	1%	160%	126%	114%	62%	
61793	148%	202%	8%	155%	180%	158%	143%	
Onondaga								
22554	-13%	-13%	13%	-8%	-22%	-6%	-29%	
61510	-16%	-16%	33%	-10%	-22%	4%	-12%	
61793	-3%	-3%	27%	6%	-9%	20%	-11%	

Notes:

* County-specific results were not available for every CPT in Table [J], as the Ingenix Database did not contain claims information for all CPTs in this listing within each county. This table presents all possible comparisons.

Table R5C: Dollar-weighted Average Percent Differences of Matches for the Top 10 CPTs by Cost (Per the 80th Percentile of the Ingenix Database) (2007)

CPT*	MAG		Medicare PSPS		PFR		PMIC	
	80 th Percentile	90 th Percentile	Mean	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	
Albany								
22554	40%	40%	39%	10%	29%	12%	18%	
61510	-35%	-35%	-16%	-28%	-38%	-17%	-29%	
Erie								
22554	-20%	-5%	15%	-14%	-13%	-12%	-21%	
61510	3%	3%	22%	14%	-2%	32%	12%	
61518	-35%	-24%	25%	-28%	-28%	-19%	-20%	
61793	40%	40%	32%	20%	35%	36%	31%	
Monroe								
22554	-7%	33%	22%	-6%	20%	-1%	13%	
47135	0%	0%	-5%	73%	32%	148%	103%	
61510	-19%	2%	13%	-23%	-5%	-8%	12%	
61793	-6%	6%	2%	3%	0%	20%	1%	
New York								
19364	158%	194%	36%	107%	95%	70%	72%	
22554	145%	176%	329%	133%	143%	111%	98%	
47135	-20%	-3%	-14%	35%	25%	67%	66%	
61343	154%	154%	265%	199%	178%	212%	165%	
61510	56%	71%	1%	65%	56%	71%	59%	
61518	101%	149%	10%	107%	127%	105%	123%	
61608	174%	174%	97%	111%	134%	78%	102%	
61682	88%	88%		160%	114%	34%	2%	
61697	90%	90%	1%	160%	126%	114%	62%	
61793	148%	202%	8%	155%	180%	158%	143%	
Onondaga								
22554	-13%	-13%	13%	-8%	-22%	-6%	-29%	
61510	-16%	-16%	33%	-10%	-22%	4%	-12%	
61793	-3%	-3%	27%	6%	-9%	20%	-11%	

Notes:

* County-specific results were not available for every CPT in Table [], as the Ingenix Database did not contain claims information for all CPTs in this listing within each county. This table presents all possible comparisons.

Table R6B: Claim-weighted Average Percent Differences of Matches Statewide for the Top 10 CPTs by Cost (Per the 80th Percentile of the 2007 Ingenix Database)

CPT	MAG		Medicare PSPS		PFR		PMIC	
	80 th Percentile	90 th Percentile	Mean	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	
19364	223%	242%	11%	187%	129%	124%	94%	
22554	85%	104%	127%	73%	79%	56%	45%	
47135	-10%	-2%	-15%	50%	24%	94%	73%	
61343	65%	65%	78%	97%	83%	96%	67%	
61510	55%	71%	31%	64%	57%	68%	59%	
61518	128%	169%	28%	142%	148%	134%	139%	
61608	174%	174%	97%	111%	134%	78%	102%	
61682	88%	88%		160%	114%	34%	2%	
61697	66%	66%	26%	127%	97%	85%	40%	
61793	84%	121%	93%	92%	106%	95%	78%	

Table R6C: Dollar-weighted Average Percent Differences of Matches Statewide for the Top 10 CPTs by Cost (Per the 80th Percentile of the 2007 Ingenix Database)

CPT	MAG		Medicare PSPS		PFR		PMIC	
	80 th Percentile	90 th Percentile	Mean	75 th Percentile	90 th Percentile	75 th Percentile	90 th Percentile	
19364	236%	252%	6%	203%	136%	135%	98%	
22554	138%	157%	203%	117%	125%	91%	77%	
47135	-10%	-2%	-15%	49%	25%	93%	73%	
61343	82%	82%	113%	115%	100%	118%	85%	
61510	87%	110%	43%	100%	93%	100%	91%	
61518	201%	253%	25%	222%	227%	208%	211%	
61608	174%	174%	97%	111%	134%	78%	102%	
61682	88%	88%		160%	114%	34%	2%	
61697	78%	78%	13%	144%	113%	100%	51%	
61793	128%	173%	169%	140%	155%	137%	116%	

Table R9B: Results of Claim-weighted Average of Matches

Benchmark	2005 ⁷	2006
MAG – 80^{th1}	30.4%	36.8%
MAG – 90^{th2}	57.6%	65.0%
Medicare PSPS – all³		36.9%
Medicare PSPS – subset^{3,4}		29.6%
NDAS⁵		-26.6%
PFR⁶		16.0%
PMIC – all⁶	13.6%	16.9%
PMIC – subset^{4,6}	22.3%	25.9%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.
 - a. Analysis excludes records for which all percentile values equaled zero or records where a lower percentile value exceeded a higher percentile value (e.g., 75th percentile value exceeded 80th percentile value).

Table R9C: Results of Dollar-weighted Average of Matches

Benchmark	2005 ⁷	2006
MAG – 80^{th1}	74.3%	117.4%
MAG – 90^{th2}	112.2%	164.1%
Medicare PSPS – all³		104.9%
Medicare PSPS – subset^{3,4}		82.2%
NDAS⁵		-13.3%
PFR⁶		60.6%
PMIC – all⁶	56.5%	61.0%
PMIC – subset^{4,6}	68.7%	74.1%

Notes:

1. Comparison of Ingenix 80th percentile value to MAG high value.
2. Comparison of Ingenix 90th percentile value to MAG high value.
3. Comparison of Ingenix Average value to Medicare Average Charge.
4. “Subset” is the collection of 30 CMS regions (29 U.S. states and Manhattan). Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips.
5. Comparison of Ingenix and Benchmark 80th percentile values.
6. Comparison of Ingenix and Benchmark 75th percentile values.
7. PFR, NDAS, and Medicare data are 2006 only.
 - a. Analysis excludes records for which all percentile values equaled zero or records where a lower percentile value exceeded a higher percentile value (e.g., 75th percentile value exceeded 80th percentile value).



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ATTACHMENT R-1: CANTOR TESTIMONY

Robin A. Cantor, Ph.D.
Principal

EXPERT TESTIMONY

In re USG Corporation et al. Debtors

Stroock & Stroock & Lavan (Official Committee of Unsecured Creditors)

- Declaration (August, 2005)

In the Matter of the Rehabilitation of the Centaur Insurance Company

Office of Special Deputy Receiver and Sidley Austin LLP (Centaur Insurance)

- Deposition (April, 2006)

Class Plaintiffs v. American Heritage Life Insurance Company et al.

Polsinelli Shalton Welte Suelthaus PC and King & Spalding (Defendants)

Missouri state court (03-CV-233109)

- Affidavit (October, 2006)

Class Plaintiffs v. American Express Company and American Express Travel Services Company, Inc.

Friedman Law Group LLP (Plaintiffs)

US District Court Southern District of New York (04 Civ. 05432 (GBD))

- Declaration (November, 2007)
- Deposition (November, 2007)
- Reply Declaration (March, 2008)

In the Matter of Dana Corporation, Debtors.

Jones Day (Debtor)

US Bankruptcy Court, Southern District of New York

- Trial Testimony (December, 2007)

In re Packaged Ice Antitrust Litigation

Spector, Roseman, Kodroff & Willis, P.C. (Class Plaintiffs)

Case No. 2:08-md-01952 (PDB) MDL No. 1952

US District Court for the Eastern District of Michigan

- Declaration (December, 2008)

**The Howard Hughes Properties and Howard Hughes Corporation v. Kern River Gas
Transmission Company**

Bracewell & Giuliani LLP (Plaintiffs/Counterdefendants)

Case No. 2:09-cv-00657-RLH-LRL

US District Court, District of Nevada

- Affidavit (October, 2009)
- Deposition (December, 2009)

TYR Sport Inc. v. Warnaco Swimwear Inc. dba Speedo USA

O'Neil LLP (Plaintiffs/Counterdefendants)

Case No. SACV 08-529-JVS(MLGx)

US District Court for the Central District of California

- Declaration (March 22, 2010)
- Declaration (April 5, 2010)
- Declaration (April 9, 2010)

ATTACHMENT R-2: MATERIALS CONSIDERED

I. MATERIALS INCORPORATED BY REFERENCE

The materials cited in the footnotes to the Expert Report of Dr. Robin Cantor in the instant matter and/or listed in Attachment 3 thereto are incorporated herein by reference.

II. LEGAL DOCUMENTS

A. Complaints

Consolidated Amended Class Action Complaint, Darlery Franco, et al. v. Connecticut General Life Insurance Co., et al. (D.N.J. filed Aug. 7, 2009).

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Deposition Transcript of Michelle Denise Ferensic-Smith (Apr. 12, 2010).

Deposition Transcript of Carla Gee (Mar. 17-18, 2010).

Deposition Transcript of Deborah Justo (ROUGH DRAFT) (Mar. 25, 2010).

C. Expert Reports

Expert Report of Bernard R. Siskin, Ph.D., Wachtel v. Health Net, McCoy v. Health Net (Mar. 31, 2004).

Expert Report of Dr. Andrew S. Joskow, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010).

Expert Report of Dr. Daniel J. Slottje on Class Certification Issues, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010).

Expert Report of Stephen Foreman, PhD, JD, MPA, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010).

Expert Witness Report of Gordon Rausser, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010).

Plaintiffs’ Expert Report dated April 6, 2010 of Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010).

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In Re Adoption of N.J.A.C. 11:3-29 by the State of New Jersey, Department of Banking and Insurance, No. A-0344-07T3 (N.J. Super. Ct. App. Div. filed Aug. 10, 2009).

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III. BATES-STAMPED DOCUMENTS

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AET-00000502 – AET-00000529.

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AET-00913905 – AET-00913906.

AET-01059346 – AET-01059373.

AET-01163366 – AET-01163367.

AET-C 0000995.

AET-C 0001038.

INGENIX 01800147 – INGENIX 01800158.

INGENIX 01801276 – INGENIX01801287.

INGENIXMDL000004623 – INGENIXMDL000004625.

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INGENIXMDL000185872 – INGENIXMDL000185872.

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INGENIXMDL000248741.

INGENIXMDL000257826 – INGENIXMDL000257888.

INGENIXMDL000451135.

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Exhibit 3

UNITED STATES DISTRICT COURT
DISTRICT OF NEW JERSEY

)
)
IN RE: AETNA UCR LITIGATION) MDL NO. 2020
) (No. 2:07-CV-3541)
)
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RESPONSIVE EXPERT REPORT OF DR. ROBIN CANTOR

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Appendix A: Additional Results

Appendix B: Federal and International Data Scrubbing Rules

Appendix C: MAG Analysis

Appendix D: High-Low Analysis

Attachment 1: Cantor CV

Attachment 2: Cantor Testimony

Attachment 3: Materials Considered

I. Qualifications

1. My name is Robin Cantor. I am a Principal in the Alexandria, VA office of Exponent, Inc. I specialize in applied economics, environmental and energy economics, statistics, and risk management. I have a B.S. in mathematics from Indiana University of Pennsylvania with a specialization in statistics and a Ph.D. in economics from Duke University with a specialization in econometrics.
2. I previously submitted an expert report in this matter (“Cantor Class Certification Report”) on April 6, 2010 and a responsive expert report (“Cantor Responsive Class Certification Report”) on May 1, 2010.¹ In this report, I am incorporating by reference the opinions expressed and analysis contained in my earlier reports. A more detailed discussion of my qualifications and curriculum vita are contained therein. A copy of my current curriculum vitae is contained in Attachment 1. My testimonial experience in the last four years is attached as Attachment 2. My current billing rate for this engagement is \$570/hour for analysis and testimony. Other Exponent staff members have also worked at my direction on this matter and they have been billed at rates ranging from \$85 to \$415/hour.

II. Assignment

3. I have been engaged by Gibson, Dunn & Crutcher LLP (“Counsel”) on behalf of its clients, Aetna Health Inc. PA, Corp., Aetna Health Management, LLC, Aetna Life Insurance Company, Aetna Health And Life Insurance Company, Aetna Health Inc., Aetna Insurance Company of Connecticut, and Aetna, Inc. (collectively, “Aetna” or “Defendants”²), to provide an expert opinion in the matters that have been consolidated as *In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation (MDL No. 2020)*.
4. Since submitting the Cantor Class Certification Report and the Cantor Responsive Class Certification Report, I received and reviewed the merit reports submitted by Plaintiffs’ experts.³ I have been asked to address the analyses and opinions contained in the reports from Plaintiffs’ experts.
5. In this MDL matter, Plaintiffs allege that (a) due to an inherent conflict of interest, the Ingenix Prevailing Healthcare Charges System (“PHCS”) Database (the “Ingenix Database”) of provider charge information was flawed in its construction and compilation, leading to systematically lower distributions of charges as reported in the Ingenix Database; and (b) when Aetna used these allegedly flawed data to determine the

¹ See Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the “Cantor Class Certification Report”); Updated Responsive Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed May 1, 2010) (the “Cantor Responsive Class Certification Report”).

² In this report, “Defendants” refers only to the referenced Aetna entities and no other parties.

³ See Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) (the “Foreman Report”); Expert Witness Report of Gordon Rausser, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) (the “Rausser Report”); and Expert Report dated August 9, 2010 of Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) (the “Siskin Report”) (collectively, the “Plaintiffs’ Experts’ Merits Reports”).

usual, customary and reasonable rates (“UCR”)⁴ for determining reimbursement of out-of-network (“ONET”) services, Aetna’s reimbursement rates for ONET services were lower than they would have been if Aetna had used a data source that did not suffer from the alleged flaws in the Ingenix Database.⁵ According to the Complaint, Aetna and other alleged co-conspirators “knowingly created, manipulated and used flawed data to set artificially low reimbursement rates for ONET.”⁶

6. The scope of my original assignment was (a) to use standard statistical and economic methods to investigate whether there is evidence that the alleged fundamental flaws in the data sampling and compilation methods resulted in a systematic downward skewing of the Ingenix Database values; (b) to investigate whether there is evidence that use of the Ingenix Database values would systematically lead to under-reimbursement on an across-the-board basis for all (or nearly all) members of the purported classes; and (c) to consider whether my findings demonstrate statistical or economic conditions that would result in fundamental conflicts among members of the proposed classes, fatal flaws in the methodology to prove class-wide impact, or both.
7. In this responsive merits report, I consider Plaintiffs’ Experts’ Merits Reports and conduct additional analysis to investigate (a) whether Plaintiffs’ experts conducted proper statistical and economic analysis to investigate the alleged downward bias of the Ingenix Database, (b) whether their collective analyses provide reliable proof that the alleged flaws in the compilation and the construction of the Ingenix Database resulted in artificially low reimbursement rates for ONET, and (c) whether analyses of Plaintiffs’ experts to demonstrate a systematic downward bias of the billed charges in the Ingenix Database provide a reliable foundation for the proffered damage calculations.
8. My opinions are based on my understanding of the information available to me as of the date of this report and my experience and training as an economist. In the event that additional relevant materials are made available to me or if Plaintiffs’ experts amend or supplement their reports, I will consider such information as necessary. I reserve the right to supplement or amend this report based upon any additional work that I might conduct or supervise from my review of such materials.
9. In conducting my analysis for this responsive report, I collected and reviewed publicly available information, case pleadings, and certain documents and depositions produced in discovery for this matter. The materials I considered for my analyses are listed in the footnotes of this report and/or in Attachment 3.

III. Summary of Findings and Opinions

10. In the Cantor Class Certification Report, I identified a number of sources of industry data that are readily available and apparently are free of the purportedly unlawful conduct

⁴ Aetna defines the reasonable and customary amount as “the prevailing charge for the service or supply in the geographic area where it is furnished.” See AET-C00103216. As was described in more detail in paragraph 25 of the Cantor Class Certification Report, the terms of Aetna’s plans vary, and reimbursement for ONET claims may be based on UCR, reasonable, usual and customary or prevailing charge plan language.

⁵ See Joint Consolidated Amended Class Action Complaint and Demand for Jury Trial, In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation (MDL No. 2020 filed Jul. 1, 2009) (the “Complaint”) at ¶ 1.

⁶ See, e.g., Complaint at ¶ 5.

alleged by Plaintiffs. I found that these data sources are appropriate benchmarks to investigate whether there is class-wide proof that the upper percentile values in the Ingenix Database are downwardly biased. Plaintiffs' experts have not offered any evidence to reject these benchmarks as measures of unbiased billed charge values. Based on the Plaintiffs' Experts' Merits Reports, there is no dispute that these benchmarks are free of the alleged unlawful conduct.

11. Using these commercial and government benchmark databases, my previous analysis showed that Ingenix Database values are frequently greater than the benchmark values. Comparisons with the benchmark databases fail to support an allegation that Ingenix Database values are lower than the benchmarks across the board. Based on my analysis of the readily available databases, I concluded that Plaintiffs reference to existing commercial and government benchmarks undermines any conclusion that there could be common impact. I also found that there was no consistent pattern of results on average across the benchmark comparisons. Using measures of simple percent-difference averages and percent-difference averages weighted by claims or estimated revenues, I found that sometimes the results were positive, negative, or effectively zero. These results fail to support a claim of a consistent systematic downward bias.
12. In their affirmative merits reports, Plaintiffs' experts have not offered any independent or reliable proof contrary to my original findings.⁷ Dr Foreman has proffered two datasets constructed from a selected set of procedures and geozips found in the contributor data used to construct PHCS. My review of Dr. Foreman's datasets reveals that they contain serious errors rendering them unsuitable for reliable analysis. Nonetheless, I go on to use, but do not adopt, his datasets as additional benchmarks in my analysis of whether there is a systematic downward bias in percentile values of the Ingenix Database. I show that when Dr. Foreman's benchmarks are compared to contemporaneous PHCS percentile values, the claim-weighted results for medical and surgical procedures fail to contradict the results I obtained for the commercial benchmarks. Analysis of Dr. Foreman's benchmarks fails to show a consistent systematic downward bias. I also show that percentile values in the Ingenix Database are sometimes higher, lower, or the same as Dr. Foreman's benchmarks.
13. Further analysis of the Ingenix Database and its collection and compilation methods supports an overall finding of no apparent downward bias. My review of publicly available information indicates that many of the methods employed to construct and compile the Ingenix Database are standard approaches used to manage large databases. Moreover, I demonstrate that some of the rules that Plaintiffs' experts find most objectionable, such as the high-low screen and the use of derived data, do not systematically bias the results downward. Where they have any impact on percentile values, there is information that indicates these practices even might lead to percentile values for the billed charges that are generally higher than the benchmark values where they have any impact on percentile values.

⁷ I note there are many statements in Dr. Foreman's report in which he claims to have found "proof" of the bias. For the reasons stated in my report herein, I find his "proof" unreliable and generally flawed in its logic and scientific foundations.

14. In contrast, Dr. Foreman has proffered a methodology to investigate the alleged bias that relies on lagged PHCS information. Even ignoring the errors in his datasets, Dr. Foreman has not created a valid foundation for the comparisons necessary to demonstrate that as an indicator of contemporaneous billed charges, the Ingenix Database is systematically biased downward. My analysis shows that this flawed methodology inflates his results of supposed downward bias. Dr. Foreman's methodology does not prove that the Ingenix Database is flawed. Rather, it demonstrates that his analysis has been manipulated to find the desired result.
15. Moreover, Dr. Foreman's benchmarks fail to solve the alleged flaws in the Ingenix Database. Previously, Dr. Foreman opined that in his view there are only two "scientific" methods to employ for the investigation of the alleged bias in the Ingenix Database—gather all the billed charge data or eliminate all of the *questionable* manipulations of input data. Neither of these methods was used by Dr. Foreman to construct his benchmarks. As a result, the data he relies upon fail both as an "internally accurate" measure under Plaintiffs' allegations and, in my opinion, as a proper benchmark for billed charge values in the world but for the challenged conduct. In particular and most conspicuously, if Plaintiffs' allegations about the Defendants' conduct are true, the contributor data suffer from the same alleged flaws as the Ingenix Database regarding representativeness, scrubbing rules, small numbers for certain procedures in particular locations, provider specialties, place of service, geographic referencing, and modifiers. Under Plaintiffs' theory, any "benchmark" created from these data will also be flawed and clearly not "internally accurate." If Plaintiffs' allegations are true, then their experts simply have compared one flawed measure of billed charges to another for the analysis of bias. Furthermore, Dr. Foreman has not demonstrated that his new methodology does not introduce new flaws to the process, such as by (a) removing data points that should not properly be removed or (b) failing to employ processes used by Ingenix that are unobjectionable and that are not challenged by the plaintiffs in this litigation (such as processes to remove duplicate data or other invalid data points). Dr. Foreman's methodology produces a new set of benchmarks for a subset of the Ingenix data points, but Dr. Foreman has failed to establish that his benchmarks are either reliable or based on scientifically sound practices.
16. Plaintiffs' experts have formed certain inferences about the alleged flaws in the collection and compilation of the Ingenix Database and the relationship to the alleged systematic downward bias of the upper percentile values. My previous and current analyses show that these inferences are based on limited and unreliable analyses. My review and analyses demonstrate that:
 - Plaintiffs' experts incorrectly infer the effect of representativeness by selecting a biased method for the analysis of the contributor data;
 - Plaintiffs' experts incorrectly infer the influence of the so-called high-low screen;

- There is information indicating that combining provider specialties and different places of service generally increases average billed charge values;
- Although Plaintiffs' experts fail to demonstrate that modifiers result in a systematic downward bias for the billed charges in the Ingenix Database, Dr. Foreman arbitrarily removes all modifier data from his benchmark data. This is improper because he failed to conduct sensitivity analysis to investigate the impact of this arbitrary decision;
- Plaintiffs' experts fail to demonstrate that the use of geozips as a geographic reference for the distribution of billed charges creates a systematic bias downward in the Ingenix Database values; and
- Empirical analysis of the derived data in the Ingenix Database indicates that these data likely have higher values than benchmark data. As a result, there is no foundation based on bias to calculate damages for these procedure/geographic area combinations.

Based on the analyses in my prior reports for this matter and my analyses of Plaintiffs' alleged flaws, I find no reliable basis to conclude that the Ingenix Database is systematically biased downward.

17. Regarding the damage methodology proffered by Plaintiffs' experts, my analysis shows that in addition to containing obvious errors, the data compiled and used by Dr. Foreman as his but-for benchmarks are biased in their construction. Dr. Foreman's benchmarks fail to correct the alleged compilation and construction flaws, have not received any independent review for their validity, cannot be replicated from his supporting files, and produce biased results for important categories of Ingenix Database values such as those for high-price but low-frequency procedures. It is highly unlikely, and Dr. Foreman has offered nothing to the contrary, that his benchmarks would exist in the world but for the challenged conduct even if corrected for their pervasive errors.
18. Most importantly, Dr. Foreman has not demonstrated that his benchmarks are unbiased, representative samples for comparison to the Ingenix Database values or for application to the subject Aetna procedure/geozip combinations. By examining only Current Procedural Terminology Code ("CPT")/geozip combinations with 255 claims or more, Dr. Foreman eliminates approximately 96 percent of the medical and surgical distributions in the Ingenix Database from his analysis of bias. In addition, Dr. Foreman's "300 CPT Study" benchmark, which is the foundation for his measure of bias used in his damages calculations, contains information for only 19 percent and 12 percent of the subject Aetna medical/surgical and dental procedure/geozip combinations, respectively.
19. In sum, there is no reason to believe, and Plaintiffs' experts have proffered no proof, that Dr. Foreman's benchmark measures approximate the but-for billed charge values.

Dr. Foreman's benchmarks are rife with errors and are neither random samples nor a census of the contributor data. They are extracted subsets with limited footprints of procedure/geozip combinations that are at issue in this matter.

20. In contrast, the collection of commercial and government benchmarks that I have identified for this matter provide coverage for all or nearly all of the medical/surgical and dental procedure/geozip combinations in the Ingenix Database and in the subject Aetna claims. There is no dispute that the commercial and government benchmarks exist in the ordinary course of business and are collected and compiled through processes independent of the challenged conduct. Association Plaintiffs in this matter have endorsed the commercial and government benchmarks as reliable reference sources for physician fee information in their documents. Standard analysis using these benchmarks refutes Plaintiffs' theory that there is a systematic downward bias in the percentile values of the Ingenix Database.
21. When the analyses sponsored by Plaintiffs' experts are corrected for a large number of the errors, biased assumptions, unsupported findings, and unreliable inferences, I show that:
 - There are no representativeness damages;
 - The results for the billed charge bias are unreliable and in any case should not be applied to claims associated with derived PHCS values;
 - The damage calculations reported by Dr. Foreman due to the alleged downward bias greatly exceed the amount implied by the damage methodology he describes; and
 - The Association damages are speculative and inconsistent with available information about job classifications and salary levels.

IV. Bases for Opinions

A. Background on Allegations and Plaintiffs' Experts' Reports

22. In order to evaluate the analysis and conclusions reached by Plaintiffs' experts regarding the Ingenix Database, it is instructive to review what Plaintiffs have alleged:

The end result of this cycle of collusion is a database that produces flawed uniform pricing schedules (effectively UCR rates) that systematically result in the under-reimbursement for ONET by Aetna and its Co-Conspirators. The flaws in the database are pervasive and include:

- (a) questionable accuracy of underlying data;
- (b) no inquiry into whether all of the contributors are using the same criteria and coding (as well as aggregating) accurately and consistently;
- (c) a procedure whereby when there is not enough charge data to provide a statistically valid sample for a CPT code, Ingenix aggregates

data from similar codes to create a large enough sample;

- (d) Ingenix itself combines geo-zips to determine what it considers to be a "sociodemographic region" and there is no verification for such regions;
- (e) Ingenix scrubs data but only removes outliers in a subjective manner, i.e., removes high-end values but not low-end outliers;
- (f) no appropriate statistical methodology (including sampling, data editing or data estimation) and as a result, data is inappropriate and biased downward;
- (g) the cumulated data that Ingenix has received has already been scrubbed by the individual contributors;
- (h) includes charges for procedures in non-comparable geographic area;
- (i) does not segregate procedures performed by providers of same or similar skill, but combines all CPT codes together;
- (j) combines ONET charges with "in-network" providers who have already agreed to a contracted rate - thus skews it downward;
- (k) fails to distinguish between the number of medical providers whose charges are reflected; and
- (l) does not edit any data that reflects negotiated or discounted charges by health providers in any given area.⁸

23. According to the text above, the Plaintiffs claim that "flaws" in the Ingenix Database are a cause of the under-reimbursement injury allegedly suffered by Plaintiffs. To investigate whether this claim has merit, Plaintiffs' experts must demonstrate that the alleged compilation and construction flaws result in billed charges reported for the upper percentiles that are systematically biased downward. Notwithstanding that none of Plaintiffs' experts rigorously define what they intend by this term or how they would determine it can be demonstrated reliably, I focus in this report on their hypotheses and analysis related to a *consistent* tendency for the upper percentile values of the Ingenix Database to be lower than values known to be free of the challenged conduct.

24. In addition, as I discuss below, none of the Plaintiffs' experts has sponsored a benchmark that is a proper indication of the Ingenix Database values but for the so-called "cycle of collusion." The benchmarks sponsored by Plaintiffs' experts are subsets of the allegedly flawed data that are inputs to the Ingenix Database with large numbers of records removed by Plaintiffs' experts. Plaintiffs' experts have not proved that the removal of these records "corrects" the influences of the challenged conduct. Nor have they proffered a dataset that likely would exist in the counterfactual world absent the challenged conduct.

1. Siskin Report

25. Dr. Siskin purports to explain in his report how a "flawed underlying methodology (including both data contribution and editing)...skews downward the amounts reported by the Ingenix Databases for the percentiles at and above the 70th percentile."⁹ He

⁸ See Complaint at ¶ 180.

⁹ See Siskin Report at p. 12.

considers the “voluntary Data Contributors,” the automatic scrubbing of data, pooling data by geozips, and the methods to calculate derived data.

26. Dr. Siskin concludes that the contribution practices allowed by Ingenix have resulted in “flawed and inadequate data,”¹⁰ but he does not provide an empirical or generalized proof that the data are biased downward. Similarly, Dr. Siskin reaches no conclusions about the direction of the bias due to data pooling or the use of geozips, although he reports a single actual case to illustrate his concerns.¹¹

Q. Does the impact of the Ingenix scrubber on the periodontist claims in Everett, Washington dictate the impact of that or any other scrubbing methodology on coronary artery bypass surgeries in New York?

A. No. What I was saying here is that, again, that the process of combining high price and low price creates the bias for the high price group. That the scrubbing process is going to tend to eliminate some valid high charges, and to the extent that you eliminate valid charges, either high or low, you are going to affect the result.

...

A. And that the -- again, the definition of the market area could affect the results. And that this is an example of all the things I said have to occur to a certain extent, the data does occur. Does it occur in every case, I never said that.

Q. Is that what you meant when you said that the same type of phenomenon applies to all CPT codes in all geographic areas?

A. Well, what I meant by that is the same problems exists every where. The extent and impact obviously varies by CPT code and area.¹²

27. In contrast, regarding automatic scrubbing of the data, Dr. Siskin concludes that “[e]ven if more valid low charges than valid high charges are removed, the Upper Percentiles will most likely be biased downward.”¹³ Dr. Siskin also concludes that Ingenix “[s]tatistically incorrectly estimates derived percentile data which biases the Upper percentile values.”¹⁴ He provides two hypothetical examples that supposedly illustrate that generally the direction of this resulting bias is downward.¹⁵ I show in section F.2 that the high-low screen can increase the percentile values relative to unscreened data and that the Ingenix derived data likely exceed benchmark values.

2. Rausser Report

28. Dr. Rausser’s report mentions hypotheses about the alleged biases only in passing. For example, he reports that “Ingenix has in some cases disregarded such modifiers in

¹⁰ See Siskin Report at p. 24.

¹¹ See Siskin Report at p. 29.

¹² See Deposition Transcript of Bernard Siskin (May 13, 2010) at pp. 356:12-357:17.

¹³ See Siskin Report at p. 13.

¹⁴ See Siskin Report at p. 16.

¹⁵ See Siskin Report at pp. 38-41.

developing its UCRs but in other cases included them, leading to potential bias and statistical error.”¹⁶

29. Dr. Rausser refers to “the systematic suppression of UCRs through the Ingenix products”¹⁷ instead of any formal analysis of the alleged bias. His analysis does not directly test whether the Ingenix Database is systematically biased downward. Instead, based on Dr. Foreman’s analysis of the Ingenix Database, Dr. Rausser concludes that “suppression has increased over time and has occurred across percentile rankings (although it is highest at the top) and across procedure types (although it is greatest for the most common and the most expensive procedures).”¹⁸ I show in section C that when matched-pair results are weighted by the 80th percentile value and therefore reflect the most expensive procedures, the Ingenix values generally exceed the benchmark values.

3. Foreman Report

30. Dr. Foreman has opined on the definitions of systematic bias and what he regards as the methods to identify and correct it:

“Systematic bias” or “systemic bias” include [sic] influences that affect the accuracy of statistical measurements. The bias is inherently internal or intrinsic. A clock that is *consistently* five minutes slow has a systematic bias. ... If bias is to be detected by comparison to an external standard that external standard must be an equivalent UCR. If the external standard is subject to the same bias – or if the accuracy of the external standard is unknown – the comparison becomes meaningless...Systematic bias can be identified and corrected by eliminating the “internal” influences that create it. If an internally accurate percentile can be identified, the bias can be identified and corrected internally.¹⁹

31. This definition and description of methods indicate that Dr. Foreman believes the measure of bias should be consistent and that accurate information should be an unbiased benchmark of the data free of the “internal” influences that comprise the challenged conduct.

32. Notwithstanding his particular view of what Plaintiffs must demonstrate for damages, Dr. Foreman’s report purports to provide the foundation for the investigation of systematic downward bias attributed to data scrubbing for outliers, modifiers, representativeness, specialties, geozip referencing, and small data counts.²⁰ In fact, Dr. Foreman only attempts to offer results consistent with a “systematic downward bias” for representativeness and data scrubbing for outliers. My analyses in sections F.1 and F.2 show that even for these two areas of Plaintiffs’ allegations, Dr. Foreman’s investigations are flawed and led him to incorrect inferences about the supposed biases.

¹⁶ See Rausser Report at ¶ 99.

¹⁷ See Rausser Report at ¶ 6.

¹⁸ See Rausser Report at ¶ 114.

¹⁹ See Responsive Report of Stephen Foreman, PhD, JD, MPA, In Re: Aetna UCR Litigation (MDL No. 2020 filed May 1, 2010) (the “Foreman Responsive Class Certification Report”) at ¶ 67, (emphasis added).

²⁰ See Foreman Report at ¶ 17.

33. Regarding the removal of outliers, Dr. Foreman advises:

Outliers may be removed from data when generating means because outliers distort means and they may be removed from models for the same reason. Outliers do not impact percentile data so there is no justification for their removal in producing percentiles. Moreover, outliers have little impact at all on large data sets. The Ingenix contributor data are immense. Outliers should not impact percentile values generated from the data.²¹

34. Based on his analysis of his interpretation of the high-low screen used by Ingenix to remove outliers, Dr. Foreman concludes:

In short, there is no scientific justification for the high-low screen. From an empirical standpoint, the high-low screen when applied to a right skewed distribution *biases higher percentile values downward*. Analysis using descriptive statistics shows how inappropriate elimination of data can bias percentile values downward. From a practical standpoint, when using percentiles to evaluate billed charges for UCR there is no justification for ignoring some billed charges merely because they are high if they provide grounds for a conclusion that the billed charges in question are reasonable.²²

35. Regarding the analysis of bias, Dr. Foreman considers the bias due to the alleged lack of representativeness separately from the bias due to the other alleged compilation flaws. He concludes:

The only way to determine whether the lack of representativeness of the Ingenix data biases billed charge percentiles downward is to obtain the population of billed charge data to compare the percentiles in the population to the percentiles in the Ingenix sample. *The population of billed charges is not currently available so no scientific investigation of bias due to lack of representativeness can be made. As noted above, estimates are possible using the Ingenix contributor data.*²³

36. Notwithstanding his admission that “no scientific investigation of bias” is possible for the alleged lack of representativeness, Dr. Foreman conducts an analysis purportedly to estimate the impact.²⁴ Based on this analysis, he calculates a 12 percent bias.²⁵ Dr. Foreman also conducts a similar representativeness test for New York State alone from which he concludes the bias is 6.6 percent.²⁶ Based on these analyses, Dr. Foreman concludes that “it would be appropriate to increase the accurate allowed damage estimates by one half to reflect problems relating to lack of representativeness of the

²¹ See Foreman Report at ¶ 197.

²² See Foreman Report at ¶ 210, (emphasis added). There is literature that demonstrates the scientific justification for removing outliers from percentile estimates. See e.g. Horn, P.S. 1990. “Robust quantile estimators for skewed populations,” *Biometrika*, 77(3): pp. 631-636; Horn, P.S. 1988. “A Biweight Prediction Interval for Random Samples,” *Journal of the American Statistical Association*, March 83(401): pp. 249-256.

²³ See Foreman Report at ¶ 277, (emphasis added).

²⁴ See Foreman Report at ¶ 277.

²⁵ See Foreman Report at ¶¶ 17,158,163,447.

²⁶ See Foreman Report at ¶ 160.

Ingenix contributor data.” I show in section F.1 that not only can the representativeness issue be investigated using Dr. Foreman’s data, but also that his data fail to provide a foundation for any damages whatsoever.

37. Dr. Foreman sponsors two databases that he constructs from the contributor data to investigate the bias due to Ingenix’s allegedly flawed methodology. His explanation of his methodology follows the general approach of matched-pair analysis:

To evaluate the effect of the Ingenix issues (apart from representativeness), we used Ingenix contributor data described above to construct billed charge percentiles free from the questionable techniques: without the high-low screen, without modifiers, in current time, with enough data to report values and without derivations. We then compared the contributor data billed charge percentiles to the percentiles contained in the products distributed by Ingenix. Since the PHCS percentiles were built from the contributor data the hypothesis [sic] for the study was that there would be no difference between the contributor data.²⁷

38. Dr. Foreman fails to address that for damage calculations, he must sponsor a benchmark that likely would exist in the counterfactual world free of the challenged conduct. This analytical requirement often supports the use of “yardstick” methods in damage analysis, which is the basic approach that I have used to investigate whether there is a systematic downward bias in the Ingenix Database.²⁸ This requirement does not imply that it is sufficient to simply remove data from the input to the Ingenix Database to construct the but-for benchmark as Dr. Foreman has done. Plaintiffs’ experts sponsor no benchmark values or methodology whatsoever to address estimated percentile values but-for the challenged conduct for the geographically referenced procedures with less than 255 claims. These geographically referenced medical and surgical distributions typically account for more than 96 percent of the Ingenix Database and 80 percent of the subject Aetna combinations. Plaintiffs’ experts implicitly assume without foundation or analysis that in the world but-for the challenged conduct, the actual billed charge is the but-for value for these procedure/geozip combinations. This assumption is contrary to the fact that all the commercial benchmarks provide estimates for nearly all these values.

39. Based on his particular benchmarks analyses, Dr. Foreman calculates downward bias estimates of 11.2 percent and 9.8 percent for medical and surgical claims and dental claims, respectively. I show in section E.2 that Dr. Foreman’s analysis is not based on a representative sample of the distributions of billed charges for the total or empirical components of the Ingenix Database or for the subject population of Aetna’s procedure/geozip combinations. I also show that his results are not based on “current time” as he states. His analysis lags the Ingenix values used in the matched pairs such that he has manipulated the impact of the alleged “questionable techniques.” I note that neither the Complaint nor the other experts for Plaintiffs allege that the Ingenix Database is flawed because it includes no forecast for inflation. I also note that the commercial and

²⁷ See Foreman Report at ¶ 278.

²⁸ See e.g. Weil, R.L., et al. 2007. *Litigation Services Handbook: The Role of the Financial Expert, 4th Edition*. Hoboken, New Jersey: John Wiley & Sons, Inc. at p. 24.12. “The yardstick approach bases the plaintiff’s experience in the but-for world on ‘the experience of a comparable firm in an actual free market.’”

government databases I used as benchmarks apparently do not include inflation adjustments and that FAIR Health is not including an adjustment for inflation.²⁹

40. Dr. Foreman states that he calculates damages using two methods:

[A] measure of damages would be the difference between what Aetna should have paid (billed charge) and what it actually paid (allowed amounts based on Ingenix, less adjustments for deductibles, copayments, coinsurance and coordination of benefits);³⁰

and

[A] measure of damages would be the difference between an "accurate" allowed amount and the amounts paid.³¹

41. Dr. Foreman defines the "accurate" allowed amount as the allowed amount increased by the measured downward bias.³² I show in section G.2 that Dr. Foreman's second method is largely a slight modification of the first method and not as he states, "a combination of amounts from (1) claims where accurate allowed was greater than allowed so that the preliminary estimate was accurate allowed less allowed and (2) claims where billed charge was less than accurate allowed so that the preliminary estimate was the billed charge less the allowed."³³

42. Finally, Dr. Foreman sponsors an analysis of damages due to the Association Plaintiffs based on "the expenses that the association plaintiffs have incurred that they would not have been required to expend "but for" defendant Ingenix's development and marketing of percentile data and defendants Aetna's use of it for UCR."³⁴ Dr. Foreman relies on "an informal survey of the Association plaintiffs" for this analysis.³⁵ I show in section G.3 that some of the salary values used by Dr. Foreman greatly exceed publicly available benchmarks. In addition, Dr. Foreman has not provided adequate supporting materials for his "informal" survey or any analysis to support that his estimated costs and categories of expense truly are incremental compared to the time and expense that the associations would expend on ONET issues but-for the challenged conduct.

B. Dr. Foreman's 300 and 350 Studies Suffer from Serious Errors

43. Dr. Foreman's report and supporting materials provide two datasets (benchmarks) that he calls the 300 Study and the 350 Study. My review shows that there are serious errors apparent in Dr. Foreman's datasets which alone make them unsuitable for use as reliable benchmarks for his bias analyses and his subsequent calculation of damages. Moreover, these errors in Dr. Foreman's basic data analysis indicate that his work product fails to

²⁹ See FAIR Health, "Summary of FAIR Health Phase I Rate Table Methodology, September 2010," available at <http://www.fairhealthus.org/sites/fairhealthus.org/files/Summary%20of%20Phase%201%20Methodology.pdf> (last visited Oct. 26, 2010) (the "FAIR Health Summary").

³⁰ See Foreman Report at ¶ 397.

³¹ See Foreman Report at ¶ 398.

³² See Foreman Report at ¶¶ 416, 418, 423, 441, 442.

³³ See Foreman Report at ¶ 423.

³⁴ See Foreman Report at ¶ 400.

³⁵ See Foreman Report at ¶ 458.

meet a minimum professional standard for reliability. In this section, I review four of the most serious errors. The first error indicates that Dr. Foreman used the same data for 2007 and 2008 in his 300 CPT benchmark. The second error indicates that Dr. Foreman failed to estimate the same percentile values for the same CPT/geozip combinations included in the 300 and the 350 benchmarks. The third error indicates that Dr. Foreman failed to compare geozips from the contributor data to batch geozips in the PHCS database properly. The fourth error indicates that Dr. Foreman failed to drop all percentile values less than \$1 as he claims and therefore his benchmarks produce incredulous simple average percent difference results.

1. 300 CPT Study Contains the Same Data for 2007 and 2008

44. My review of Dr. Foreman's production materials, which remain incomplete at the time of this report,³⁶ indicates that he made a substantial error in compiling his 300 CPT Study data. Table 1 shows my comparison of his 2007 and 2008 data for the 63,790 CPT/geozip combinations that appear in the datasets for both years. The table demonstrates that on all standard summary statistics and his reported percentile values, the data for the two years are identical.

Table 1: Foreman Medical/Surgical Contributor Data Comparison, 2007 to 2008

Foreman Contributor Data 2007 ¹									
Statistic	Count	50th Percentile	60th Percentile	70th Percentile	75th Percentile	80th Percentile	85th Percentile	90th Percentile	95th Percentile
Count	63,790	63,790	63,790	63,790	63,790	63,790	63,790	63,790	63,790
MIN	255	-	-	-	\$0.01	\$0.01	\$0.01	\$0.01	\$0.01
MAX	3,160,819	\$5,155.23	\$5,155.23	\$7,099	\$7,099	\$8,352	\$8,816.94	\$11,858.48	\$12,902
Mean	11,512	\$157.29	\$170.51	\$187.26	\$198.31	\$212.67	\$231.07	\$257.39	\$303.57
Std. Dev.	40,992	\$281.74	\$307.22	\$343.09	\$368.65	\$403.84	\$447.89	\$514.71	\$625.72

Foreman Contributor Data 2008 ²									
Statistic	Count	50th Percentile	60th Percentile	70th Percentile	75th Percentile	80th Percentile	85th Percentile	90th Percentile	95th Percentile
Count	63,790	63,790	63,790	63,790	63,790	63,790	63,790	63,790	63,790
MIN	255	-	-	-	\$0.01	\$0.01	\$0.01	\$0.01	\$0.01
MAX	3,160,819	\$5,155.23	\$5,155.23	\$7,099	\$7,099	\$8,352	\$8,816.94	\$11,858.48	\$12,902
Mean	11,512	\$157.29	\$170.51	\$187.26	\$198.31	\$212.67	\$231.07	\$257.39	\$303.57
Std. Dev.	40,992	\$281.74	\$307.22	\$343.09	\$368.65	\$403.84	\$447.89	\$514.71	\$625.72

Notes

1 Source for 2007 data: Excel File "Comp Ing_07_02.xlsx" - "medsurg07" tab

2 Source for 2008 data: Excel File "Comp Ing_08_08 Rev.xlsx" - "MEDSURG" tab

45. Given that the contributor data are added monthly, it is virtually impossible that percentile and other statistical data for 63,790 combinations would be identical in two years. In addition, my review of the contributor data included in Dr. Foreman's production materials indicates that this data source, i.e., his input data for compiling the

³⁶ See, e.g., Letter from Geoffrey Sigler, to Robert J. Axelrod and W. Tucker Brown, Re: Answers given to Defendants questions Sep. 24, 2010 (Oct. 1, 2010); Letter from Geoffrey Sigler, to Robert J. Axelrod and W. Tucker Brown, Re: Dr. Foreman's "Production Roadmap" (Oct. 1, 2010); Excel File "Production Roadmp.xlsx". In his "Production Roadmap", produced on Sep. 13, 2010, Dr. Foreman reports that (1) he "lost" production materials such as those that would have supported "Table 13" and "Table 27", (2) he performed analytical procedures "manually" without producing any underlying computer code such that they cannot be replicated (such as "Manually eliminate non NY lines" related to analysis for "Table 3", and (3) "code [was] not kept," as reported for "Table 8".

300 Study, are not the same for 2007 and 2008. Therefore, percentile values and summary statistics for the 63,790 combinations in 2007 and 2008 should differ. Clearly, Dr. Foreman's 300 CPT Study is based on a faulty dataset. Since this benchmark is the foundation for his bias analysis, I conclude that all of his subsequent findings and conclusions based on it are unreliable.

2. 300 CPT and 350 CPT Study Data Fail to Match for the Same CPT/Geozips

46. My review of Dr. Foreman's 300 CPT benchmark data could not establish whether his data for 2007, 2008, or both were invalid. I could only establish the error by comparing the combinations in both years *within* the 300 Study. I conduct further review of the materials produced by Dr. Foreman for his 300 and 350 CPT Studies to investigate 2007 data *across* his benchmarks. My analysis indicates that he has errors in the data for CPT/geozip combinations that appear in both benchmarks. Examining the overlapping combinations, I find claim count and percentile results for individual CPT/geozip combinations that are not consistent. For example, Dr. Foreman reports in his production that CPT 96413 (Chemotherapy Administration, Intravenous Infusion Technique; Up to One Hour, Single or Initial Substance/Drug) in geozip 776 (Beaumont, Port Arthur, TX) has an 80th percentile value of \$622 and claim count of 1,159 in the 300 CPT Study but an 80th percentile value of \$250 and 289 claims in the 350 CPT Study.³⁷
47. Additional examples of this type of error are reported in Table 2. It is unlikely, however, that these errors are caused by the faulty 2007 data in the 300 CPT Study that I discussed in the last subsection because the claim count and values for the 80th percentile are substantially different. The table also reflects that Dr. Foreman sometimes recorded the wrong value from PHCS as shown in the last two columns of the first row of the table data.

³⁷ This analysis was performed by comparing the following files from Dr. Foreman's production: "Comp 300 Ing_07_02 Rev.xlsx," which I understand was used to generate some results in Foreman "Table 20" and Foreman "Table 22" and "Compare_Contrib_2007_1.xlsx," which I understand was used to generate some results in Foreman "Table 25".

Table 2: Examples of Different Data for the Same CPT/Geozip Across Studies

Procedure Code	Geozip	80 th Percentile							
		Count		Contributor Data		'Foreman' PHCS		Actual PHCS ³	
		300 CPT ¹	350 CPT ²	300 CPT ¹	350 CPT ²	300 CPT ¹	350 CPT ²		
78480	86	4,000	554	\$210	\$2,194	\$200	\$70	\$200	
81002	180	13,723	942	\$16	\$146	\$15	\$15	\$15	
83540	24	2,132	297	\$204	\$18	\$18	\$18	\$18	
95165	985	15,864	347	\$360	\$18	\$18	\$18	\$18	
99070	469	6,688	342	\$220	\$35	\$41	\$41	\$41	

Notes:

1. Source for data: 300 Study - Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07".

2. Source for data: 350 Study - Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1".

3. Source for data: PHCS 2007 release 2.

48. Table 3 provides a summary of the discrepancies found by comparing 2007 data for overlapping CPT/geozip combinations in the 300 and 350 Studies.³⁸ There are 31,907 common combinations in both studies. The total claim count for these overlapping combinations in the 300 CPT Study is substantially larger than the count in the 350 data for the same group of CPT/geozip combinations (approximately 567 million claims versus 264 million claims). Moreover, the claim count for the 300 Study exceeds the count in the 350 Study for approximately 95 percent of the combinations. Across the overlapping combinations, the average 80th percentile value of the 300 Study exceeds the value in the 350 Study (i.e., \$181.38 versus \$177.16).

³⁸ I use 2007 for the comparisons because Dr. Foreman provided annual data only for this year for both benchmarks.

**Table 3: 300 CPT v. 350 CPT Footprint
-2007**

	300 Footprint²	350 Footprint³
Number of common CPT/Geozips²	31,907	
Proportion of CPT/Geozips for which claim count is:		
300>350	94.7%	
300=350	0.02%	
300<350	5.3%	
Number of common claims	566,693,128	264,343,928
Avg. claim count per CPT/Geozip	17,761	8,285
Avg. 80th percentile fee value	\$181.38	\$177.16

Notes:

1. 16 matches excluded due to \$0 value for 80th percentile. Rounding in the 350 dataset may have resulted in these values.

2. Source for data: Source for data: 300 Study - Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07".

3. Source for data: 350 Study - Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1".

49. Other reasons to question the reliability of Dr. Foreman's data in the 300 and 350 Studies are based on observed inconsistencies in his methods to compile the datasets. For example, beginning with the 350 CPT Study, I reviewed Dr. Foreman's analysis of 80th percentile values in the 2007 350 Study relative to PHCS 2006 Release 2, reported in Foreman Report "Table 25". Dr. Foreman reports in "Table 25" that he used 46,404 CPT/geozip combinations in his 350 analysis and found a 12.7% weighted average percent difference between his benchmark 80th percentile values and the PHCS 2006 Release 2 80th percentile values.³⁹

50. In his "Production road map.xlsx," Dr. Foreman reports a file used as an intermediate step in his 350 Study.⁴⁰ This file contains contributor percentile values for 156,290 CPT/geozips for 2007. Dr. Foreman appears to have eliminated 74,584 combinations because the contributor count was less than 255 claims. An additional 236 combinations likely were eliminated because percentile values calculated by Dr. Foreman were less than \$1. When I extract data from PHCS for 2006 Release 2, I am able to find 80,393 CPT/geozip combinations with valid PHCS 80th percentile values. Based on my review I found:

- There were 1,077 CPT/geozip combinations in Dr. Foreman's intermediate dataset that I could not find in the PHCS 2006 Release 2 database.⁴¹
- Due to incorrectly matching contributor geozips to PHCS batch geozips, Dr. Foreman excluded 26,557 CPT/geozips from his analysis presented in Foreman Report "Table 25",

³⁹ See Excel File "Compare_Contrib_2007_1.xlsx". This file reports data for 46,403 CPT/geozip combinations, rather than 46,404.

⁴⁰ See Excel File "contrib_2007_percentiles.csv".

⁴¹ It would be appropriate to exclude these CPT/geozip combinations from analysis.

- An additional 7,539 CPT/geozip combinations were excluded without explanation, and
- Dr. Foreman's 46,403 CPT/geozip combinations include 98 that had an 80th percentile value less than \$1 and eight combinations that had no match in the PHCS database that should have been excluded, under his sponsored methodology.

51. Overall, Dr. Foreman used only 58 percent of the valid data he purports to have selected to calculate his weighted average percent difference for 2007 compared to PHCS 2006 Release 2.

52. Reviewing the 46,403 CPT/geozip combinations used for the results reported in Foreman Report "Table 25", I find that 4,348 CPT/geozip combinations (9.4%) have higher 80th percentile values in the PHCS database than used by Dr. Foreman, four (0.01%) have lower 80th percentile values, and 41,945 (90.6%) are the same.

53. Additionally, I performed the same review of Dr. Foreman's analysis of 80th percentile values from 2007 contributor data relative to Ingenix PHCS 2007 Release 1 for the 300 CPT Study, reported in Foreman Report "Table 20". Dr. Foreman reports that he used 63,812 CPT/geozip combinations in his analysis and found a 15.0% weighted average percent difference between his contributor 80th percentile values and the PHCS 2007 Release 1 80th percentile values.⁴²

54. Dr. Foreman also produced an Excel file that appears to contain his full set of procedure code-geozip combinations extracted for the 300 CPT Study for 2007.⁴³ This file contains contributor percentile values for 83,329 procedure code-geozip combinations for 2007. The 63,812 combinations in Foreman Report "Table 20" is a subset of this file.⁴⁴ When I extract data from Ingenix PHCS 2007 Release 1, I am able to find 65,363 CPT/geozip combinations with valid Ingenix PHCS 80th percentile values. My analysis shows:

- There are an additional 2,363 combinations beyond those used by Dr. Foreman for the analysis presented in Foreman Report "Table 20". Dr. Foreman provides no explanation in his report for why he excludes the remaining 2,358 valid CPT/geozip combinations,
- For eight of these 2,363 CPT/geozip combinations, Dr. Foreman reports an 80th percentile value that equals the 80th percentile value I find in the PHCS Database. For the remaining 2,355 CPT/geozips Dr. Foreman reports a "NULL" value, and

⁴² See "Comp 300 Ing_07_02 rev.xls" tab "medsurg07."

⁴³ See "Ingenix 2007 contributor versus published for top 300 Codes in top 300 GeoAreas," produced via Hard Drive on August 20, 2010 in folder "300 CPT Study." Similarly-named files were produced or 2006 and 2008. The 2007 file and the 2008 file are identical.

⁴⁴ The includes 83,268 CPTs, as well as 42 CDTs that Dr. Foreman uses in his "overall" analysis presented in Foreman Report "Table 19" and "dental" analysis presented in Foreman Report "Table 21" and 20 HCPCS that Dr. Foreman uses in his "overall" analysis presented in Foreman Report "Table 19."

- For five of the CPT/geozip combinations for which Dr. Foreman reports a “NULL” value for the Ingenix PHCS 80th percentile, Dr. Foreman calculates an 80th percentile for the contributor data of \$0.01.⁴⁵ Under Dr. Foreman’s stated rule of calculating percentiles using contributor billed charges greater than or equal to \$1, these combinations would have been excluded from his analysis. I address this error more completely below.

3. 350 CPT Study Suffers From Improper Matching of Batch Geozips to PHCS

55. My review of Dr. Foreman’s production materials indicates that Dr. Foreman uses different techniques in the 300 and the 350 Studies to compare data with PHCS. For example, the percentile values based on the contributor data for geozips 776 and 777 should be compared to the values from the batch geozip 776 used by Ingenix in the PHCS module. Dr. Foreman’s programs appear to indicate that this comparison process was performed in the 300 CPT Study—creating a matched pair for 776 and 777—but not performed in the 350 CPT Study.⁴⁶ Rather, in the 350 CPT Study only geozip 776 was compared to the Ingenix batch geozip 776 and Dr. Foreman essentially eliminated the percentile values and counts from geozip 777 from the matched pairs used for the 350 Study. In fact, of the “450 geozips with the most claims”⁴⁷ selected by Dr. Foreman, he dropped from his analysis every CPT/geozip combination with a secondary geozip.⁴⁸ Table 4 reports the count of geozips in the 350 CPT Study in batch geozips which include two or more geozips—the definition of a PHCS batch geozip. Although Dr. Foreman kept nearly all of the first geozips in a batch for his analysis, he dropped all CPT/geozip combinations for 174 geozips that were listed second or later in the ordering of a batch geozip but that represented valid comparisons to PHCS.

⁴⁵ The five CPT/geozip combinations for which Dr. Foreman has calculated a \$0.01 80th percentile are all in geozip 274. This is a broader problem for Dr. Foreman’s data as I discuss in the following subsection.

⁴⁶ Dr. Foreman’s Excel File “Production Roadmap.xlsx” reports that he performed the comparison process manually within the software program SPSS for the 350 CPT Study. Therefore, he produced no computer code to indicate how he made his comparisons in the 350 Study.

⁴⁷ See Foreman Report at ¶ 337

⁴⁸ I use the term “secondary geozip” to refer to a geozip that is listed second or later in the ordering within a batch geozip. For example, batch geozip 776, TX-BEAUMONT, PORT ARTHUR (776-777), includes first geozip 776 and secondary geozip 777.

Table 4: Count of Geozips in 350 CPT Study by Batch Geozip Order

Geozip Batch Order	Count of Geozips	
	Selected from Contributor Data for 350 CPT Study	Count of Geozips Used in Foreman "Table 25"
First Geozip in Batch	113	112
Secondary Geozips in Batch	174	0

Notes:

1. Source for data: 350 Study - Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1" and Excel File "contrib_2007_percentiles.csv" tab "contrib_2007_percentiles".

4. Dr. Foreman Failed to Eliminate Billed Charges Less Than \$1.00

56. Benchmark data will be inaccurate if the percentile values are incorrectly recorded from PHCS or the contributor data. In such cases the matched pairs used in any subsequent bias analysis will be unreliable. Dr. Foreman datasets contain percentile values that are so inconsistent with the PHCS values that they suggest data reporting errors, percentile recording errors, or both. My review of the materials produced by Dr. Foreman to calculate percent differences for his bias analysis indicates not only that he made errors in estimating the percentile values but also in extracting information from PHCS.

57. Dr. Foreman reports that he “eliminated claims with negative values, zero values and values less than \$1 for billed charges.”⁴⁹ My review of his 300 and 350 CPT benchmarks indicates that he did not. Table 5 shows the number of times that Dr. Foreman estimated suspicious percentile values for the contributor data and included the results in the 300 and 350 CPT Studies.

⁴⁹ See Foreman Report at ¶ 292. In his deposition, Dr. Foreman testifies initially that “we dealt with some issues in the data such as negatives and zeros and claims less than a dollar as described in the report.” See Deposition Transcript of Stephen Foreman (ROUGH) (Nov. 1-2, 2010) (the “Foreman Merits Deposition”) Volume I at pp. 93:15-18. (See also Foreman Merits Deposition Volume I at pp. 152:4-8.) He explains that CPT/geozips with percentile values equal to \$0.01 were excluded because “they don’t make much sense” (Foreman Merits Deposition Volume I at pp. 152:25 – 154:12). Dr. Foreman later explains that in the 350 CPT Study he excluded only CPT/geozips with claims less than zero, not less than \$1. (Foreman Merits Deposition Volume I at pp. 236:16-18, 194:6-11). I observe in Dr. Foreman’s datasets that in addition to retaining percentile values equal to \$0.01, he also retained CPT/geozips with small values for percentiles such as \$0.04 and \$0.05. If it does not make sense to include percentile values equal to one penny, then the same logic should hold for values between one penny and one dollar.

Table 5: Count of Medical/Surgical CPT/Geozip Combinations with Percentile Value < \$1

Study	Contributor Data Year	PHCS Year & Release	Number of CPT/Geozips with a Contributor Percentile Value < \$1
300	2006	2005 R2	0
		2006 R1	0
	2007	2006 R2	107
		2007 R1	124
350	2006_1 ²	2005 R2	32
		2006_2 ²	25
	2007	2006 R2	98
		2007 R2	63
	2008_1 ²	2008 R1	76
	2008_2 ²		

Notes:

1. 300 Study counts sourced from the following files produced by Dr. Foreman for Contributor Data Years 2006, 2007 & 2008 respectively: 2006 - Excel File "Compare 300 CPT 2006_2.xlsx" tabs "Ing 2005 v2" & "Ing 2006 v1"; 2007 - Excel File "Comp 300 Ing_07_02 Rev.xlsx" tabs "medsurg06" & "medsurg07"; 2008 - Excel File "Comp 300 Ing 08 rev.xlsx" tab "2007med", Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "MEDSURG".
2. "2006_1" refers to the first six months of 2006. Similarly, "2006_2" refers to the second six months of 2006. The same applies to 2008.
3. 350 Study counts sourced from the following files produced by Dr. Foreman for Contributor Data Years 2006_1, 2006_2, 2007, 2008_1, & 2008_2 respectively: 2006_1 - Excel File "Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1"; 2006_2 - Excel File "Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B"; 2007 - Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1"; 2008 - Excel File "350 2008_1 compare rev.xlsx" tab "Steve 2008_1 compare rev", Excel File "350 2008_2 Compare Rev.xlsx" tab "Steve 2008_2 Compare Rev" .

58. In summary, my review revealed so many serious errors with the construction of Dr. Foreman's datasets that they fail to support even a minimum level of confidence in their analytical reliability.⁵⁰ In addition to the obvious data errors, the datasets also suffer from representativeness and scope issues making them particularly unsuitable for Dr. Foreman's analysis of the alleged bias. I address those issues in later sections of this report. In the next section, I ignore my findings of obvious errors and use Dr. Foreman's

⁵⁰ There are many additional categories of errors in Dr. Foreman's report and production materials. For example, he has mathematical and typographical errors, includes the wrong values from his production materials or his report tables do not match any values in production materials, cites to textbooks that do not include the subject material cited, applies rules inconsistently for excluding billed charges from calculation of percentile values or for excluding CPT/geozip combinations from his analysis, mislabels tables, and mismatches values stated within the text of his report and in his tables.

300 and 350 Study datasets as he provided them. Essentially, I am using, but not adopting, these data as benchmarks for the investigation of the alleged bias “as is.”

C. Contemporaneous Matched Pairs Analysis Using Dr. Foreman’s Benchmarks “As Is” Fails to Support a Consistent Systematic Downward Bias

59. In this section, I use Dr. Foreman’s datasets “as is” to investigate their implications for investigating the alleged systematic downward bias of the Ingenix Database. In particular, I consider whether Dr. Foreman’s analyses using his 300 and 350 Studies alter the results that I found previously by using the commercial and government benchmarks. One important difference between my methodology and that of Dr. Foreman is the focus on a contemporaneous comparison of PHCS values to any particular benchmark. I show below that using contemporaneous data, comparisons between Dr. Foreman’s benchmarks and PHCS percentile values for medical and surgical procedures fail to support Plaintiffs’ allegations of a systematic bias downward.
60. As a component of my investigation of class-wide proof of injury in the Cantor Class Certification Report, I compared the upper percentile Ingenix Database values with values from the commercial products and the distribution average with the average value in Medicare PSPS. My analysis compared “matched” values for a particular CPT or Current Dental Terminology Code (“CDT”) in a particular geographic region.
61. I constructed a percent difference measure that was used by the New York Attorney General’s Office (“NYAG”) in its reported analysis of the Ingenix Database.⁵¹ Specifically this measure is the difference between the Ingenix Database value and the benchmark value as a proportion of the benchmark value: $(I - B)/B$.⁵² I estimated the simple average, claim-weighted average, and revenue-weighted percent difference results for my comparisons by reference to the total claim and average price data for procedure/geozip combinations in the Ingenix Database. I conducted my analysis of bias on a contemporaneous basis as did the NYAG study.
62. My analysis of matched pairs for services by geographic areas on a national basis indicates that, when the Ingenix Database values are compared to the commercial and government benchmarks, the average percent differences are either (a) positive, which indicates that Ingenix values, on a national basis, tend to be higher than the benchmark, or (b) when the average percent differences are negative, they tend to be very small. These results do not support Plaintiffs’ theory of a common or systematic downward bias.
63. I have supplemented my analysis of matched pairs using the set of CPT/geozips used by Dr. Foreman in his 300 and 350 Studies. I have, however, modified Dr. Foreman’s analysis to reflect (a) a contemporaneous comparison between values in the Ingenix Database and the benchmark, (b) my measure of percent difference; and (c) weights

⁵¹ See State of New York, Office of the Attorney General, “Health Care Report: The Consumer Reimbursement System is Code Blue,” (Jan. 13, 2009) at p. 20 (Table 2 and Table 3), (“The NYAG Report”). The NYAG Report does not describe the calculation used to produce its percent differences. However, the percent differences in the NYAG Report Table 2 and Table 3 can be replicated using the following formula: $(I-B)/B$, where I refers to the Ingenix Database and B refers to the benchmark data collected).

⁵² In contrast, Dr. Foreman uses $(B - I)/I$. This makes a slight difference in the absolute value of the results, but a large difference in the interpretation of the sign of the results.

based on claim counts in the Ingenix Database.⁵³ These results are presented in Table 6. The table shows the claim-weighted matched pair results for various benchmarks and the PHCS percentile values. It also varies the footprint of the matched-pair comparisons; i.e., from Dr. Foreman's selected set of procedure/geozip combinations to all empirical and derived combinations in the Ingenix Database. A positive percent difference indicates that for the average claim in the footprint, the Ingenix percentile value exceeds the benchmark value for the same percentile. A negative percent difference indicates that for the average claim in the footprint, the Ingenix percentile value is less than the benchmark value for the same percentile.

64. The results from Dr. Foreman's medical and surgical benchmarks, shown in the eighth row of the table are not consistently negative, and when they are negative, they are small—all less than 5 percent. The claim-weighted results based on Dr. Foreman's footprints are not substantially different from the results obtained with the commercial and government benchmarks.

Table 6: Percent Difference Benchmark Analysis – Claim Weighted

Benchmark	Average Percent Differences 300 CPTs ⁸			Average Percent Differences 350 CPTs ⁹			All Empirical CPTs ^{1,10}			All Empirical & Derived CPTs ¹⁰			
	2006	2007	2008 R1	2006 R1	2006 R2	2007	2008	2005	2006	2007	2005	2006	2007
PFR - 75 th Percentile ⁶	-2.2%	-2.2%			-1.3%	-1.0%		-2.6%	-3.4%		-2.5%	-3.4%	
PMIC - 75 th Percentile ⁶	0.5%				1.5%			-0.8%	0.8%		-0.7%	0.9%	
PMIC Subset - 75 th Percentile ^{6,7}	11.1%				13.2%			8.1%	10.8%		8.1%	10.8%	
MAG - 85 th Percentile ²	-0.9%				-0.5%			9.0%	-1.8%		9.1%	-1.7%	
MAG - 90 th Percentile ³	4.9%				5.2%			15.2%	3.8%		15.3%	3.9%	
Medicare PSPS - Mean ⁴	8.2%	7.7%			8.5%	5.8%		7.9%	6.9%		8.0%		
Medicare PSPS Subset - Mean ^{4,7}	8.1%	9.5%			8.9%	9.1%		7.8%	8.7%		7.8%		
Foreman Medical/Surgical - 80 th Percentile ⁵	-2.8%	-0.6%	3.7%	-1.7%	-1.3%	-4.0%	-1.1%						

Notes:

1 2005 & 2006 All Empirical CPT percent difference values taken from Tables 15, 16 & 17 of the Expert Report of Robin Cantor, In Re: Aetna UCR Litigation (MDL No 2020 filed Apr 6, 2010) except for MAG - 85th Percentile values

2 Comparison of PHCS 85th percentile value to MAG high value

3 Comparison of PHCS 90th percentile value to MAG high value

4 Comparison of PHCS Average value to Medicare Average Charge

5 Comparison of PHCS and Foreman Benchmark 80th percentile values

6 Comparison of PHCS and Benchmark 75th percentile values

7 "Subset" is the collection of 30 CMS regions (29 US states and Manhattan) Each of these CMS regions perfectly matches an Ingenix region—i.e., the CMS region completely contains and consists of a collection of geozips

8 Source for data: 300 Study - Excel File "Compare_300_CPT_2006_2.xlsx" tab "Ing 2006 v1", Excel File "Comp_300_Ing_07_02_Rev.xlsx" tab "medsurg07" & Excel File "Comp_300_Ing_08_08_Rev.xlsx" tab "MEDSURG"

9 Source for data: 350 Study - Excel File "Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1", Excel File "Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B", Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1" & Excel File "350_2008_1_compare_rev.xlsx" tab "Steve_2008_1_compare_rev"

10 Source for data: All Empirical and All Empirical & Derived - PHCS 2005 - 2007

65. Additional information supports that the medical and surgical values in the Ingenix Database are not consistently lower than Dr. Foreman's benchmark values when compared contemporaneously. Table 7 shows state-by-state analysis that indicates there are twenty-four to forty-five states where the majority of CPT/geozips in Dr. Foreman's

⁵³ The work product provided by Dr. Foreman shows that he uses contributor claim count in his weighted average percent different calculations in the 300 CPT Study. However, the work product provided by Dr. Foreman does not identify the source of the claim count in the backup files for the 350 Study. Therefore, whether Dr. Foreman uses contributor or Ingenix PHCS claim count as the weight cannot be verified.

footprints have 80th percentile PHCS values equal to or greater than Dr. Foreman's 80th percentile values in 2006 and 2007.⁵⁴ Table 8 shows the results for the 300 Study comparisons by state.⁵⁵

Table 7: Count and Proportion of U.S. States for Which PHCS 80th Percentile ≥ Foreman 350 CPT Study 80th Percentile for Majority of CPT / Geozips, by Year

Year	States ¹	Count	Proportion of states covered by Foreman 350 CPT Study ²
2006 1 ³	AL, AR, CA, CO, CT, DC, DE, FL, GA, IA, KS, KY, LA, MD, MS, MT, NC, NM, NY, OH, RI, SC, TX, VA	24	51%
2006 2 ⁴	AK, AL, AR, AZ, CA, CO, CT, DE, FL, GA, IA, ID, IL, IN, KS, KY, LA, MA, MD, ME, MI, MN, MO, MS, MT, NC, ND, NE, NH, NJ, NM, NY, OH, OK, OR, PA, RI, SC, SD, TN, TX, UT, VA, VT, WI	45	96%
2007 ⁵	AK, AL, AR, AZ, CA, CO, CT, DC, DE, FL, GA, IA, IL, IN, KS, KY, LA, MA, MD, ME, MI, MS, MT, NC, ND, NH, NM, NY, OH, OK, OR, PA, RI, SC, SD, TN, TX, UT, VA, VT, WA, WI	42	89%
2008 ⁶	LA, MD, WY	3	6%

Notes:

1 Included are states where 50% or more of CPT/geozip combinations have Ingenix 80th percentile values greater than or equal to the Foreman 350 CPT Study 80th percentile value for that same CPT/geozip combination

2 The Foreman 350 Study includes 46 states and the District of Columbia for 2006 1, 2006 2 and 2007. Missing are HI, NV, WV and WY. For 2008, Dr. Foreman expands his scope and thus captures all 50 states and the District of Columbia

3 Foreman data for first half of 2006 compared to PHCS 2006 Release 1. Source: Excel File "Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1"

4 Foreman data for second half of 2006 compared to PHCS 2006 Release 2. Source: Excel File "Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B"

5 Foreman data for 2007 compared to PHCS 2007 Release 2. Source: Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1"

6 Foreman data for first half of 2008 compared to PHCS 2008 Release 1. Source: Excel File "350 2008_1 compare rev.xlsx" tab "Steve 2008_1 compare rev"

⁵⁴ My analysis of Dr. Foreman's 350 Study data eliminates any records for which his 80th percentile value is zero. This is a conservative assumption for the results in Table 7.

⁵⁵ Because it appears that Dr. Foreman used the same contributor percentile values for 2007 and 2008, there may actually be more than four states where the majority of CPT/geozips in Dr. Foreman's study have 80th percentile values equal to or greater than the 80th percentile values in the PHCS database in 2007.

Table 8: Count and Proportion of U.S. States for Which PHCS 80th Percentile ≥ Foreman 300 Study 80th Percentile for Majority of CPT / Geozips, by Year

Year	States ¹	Count	Proportion of states covered by Foreman 300 CPT Study ²
2006 ³	AL, AR, AZ, CA, CO, CT, DE, FL, GA, IN, KS, KY, LA, MA, MD, MS, NC, ND, NH, NJ, NM, NY, OH, OK, RI, SC, TX, VA	28	61%
2007 ⁴	AR, MD, NM, TX	4	9%
2008 ⁵	AR, GA, KS, LA, MD, NM, OK, SC, TN, TX	10	22%

Notes:

1. Included are states where 50% or more of CPT/geozip combinations have Ingenix 80th percentile values greater than or equal to the Foreman 300 CPT Study 80th percentile value for that same CPT/geozip combination.
2. The Foreman 300 Study includes 45 states and the District of Columbia. In 2006 are ID, ME, HI, VT, and SD are missing. In 2007 and 2008, MT, ME, HI, VT, and SD are missing.
3. Foreman data for 2006 compared to PHCS 2006 R2. Source: Excel File "Compare 300 CPT 2006_2.xlsx" tab "Ing 2006 v1".
4. Foreman data for 2007 compared to PHCS 2007 R2. Source: Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07".
5. Foreman data for 2008 compared to PHCS 2008 R1. Source: Excel File "Comp 300 Ing 08 rev.xlsx" tab "2007med".

66. Regarding the bias results reported by Dr. Foreman, I find that he has not conducted a direct test of the alleged systematic downward bias. He has obscured his bias results by introducing an additional factor that might lead to an upward bias in Dr. Foreman's benchmarks. Moreover, by combining his lagged factor with all other potential sources of his estimated bias, Dr. Foreman cannot separate the root causes of the alleged injuries suffered by Plaintiffs should some of the collection and compilation flaws be found lawful by the Court. As a result, Dr. Foreman's methodology is not suitable if the need arises to segregate damages by the specific flaws alleged by Plaintiffs.

67. I can partially isolate the effect of Dr. Foreman's lagged comparisons by defining as "Less" comparisons for which the PHCS percentile value is less than Dr. Foreman's benchmark. I define "Greater or Equal" as comparisons for which the PHCS value is greater than or equal to Dr. Foreman benchmark. Tables 9 and 10 show that percentage share is consistently moved from the "Less" column to the "Greater or Equal" column when the comparison is not lagged.

Table 9: Frequency Proportions for Foreman 300 CPT Footprint v. Ingenix Releases, 2006-2008

Contributor Data Year	Comparison	Greater or Equal ²	Less
	PHCS Release		
2006	2005_2 ¹	35.3%	64.7%
	2006_1 ¹	42.3%	57.8%
	Contemporaneous ³	53.6%	46.4%
2007	2006_2 ¹	30.7%	69.3%
	2007_1 ¹	34.1%	65.8%
	Contemporaneous ³	38.5%	61.5%
2008	2007_2 ¹	38.5%	61.5%
	Contemporaneous ³	43.9%	56.1%

Notes:

1. As reported by Dr. Foreman. "Greater" & "Less" reversed from as reported by Dr. Foreman to mean Ingenix greater than contributor rather than contributor greater than PHCS. Source: Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 22.

2. "Greater or Equal" = "Greater" + "Equal".

3. The "Contemporaneous" comparison is the comparison between Dr. Foreman's benchmark and the most contemporaneous release of PHCS available. These are the following comparisons: 2006:2006_2, 2007:2007_2, 2008:2008_1. Source for Foreman Footprint data: Excel File "Compare 300 CPT 2006_2.xlsx" tab "Ing 2006 v1", Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07" and Excel File "Comp 300 Ing 08 rev.xlsx" tab "2007med".

Table 10: Frequency Proportions for Foreman 350 CPT Footprint v. Ingenix Releases, 2006-2008

Contributor Data Year	Comparison PHCS Release	Greater or Equal ²		Less
		Greater or Equal ²	Less	
2006	2005_2 ¹	44.2%	55.8%	
	2006_1 ¹	39.6%	60.4%	
	Contemporaneous ³	61.2%	38.8%	
2007	2006_2 ¹	41.0%	59.0%	
	2007_1 ¹	37.4%	62.6%	
	Contemporaneous ³	58.0%	42.0%	
2008	2007_2 ¹	34.9%	65.1%	
	2008_1 ¹	38.7%	61.3%	
	Contemporaneous ³	41.6%	58.4%	

Notes:

1. As reported by Dr. Foreman, "Greater" & "Less" reversed from as reported by Dr. Foreman to mean Ingenix greater than contributor rather than contributor greater than PHCS. Source: Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 26.

2. "Greater or Equal" is the sum of percents for "Greater" and "Equal".

3. The "Contemporaneous" comparison is the comparison between Dr. Foreman's benchmark and the most contemporaneous release of PHCS available. These are the following comparisons:

2006:2006_2, 2007:2007_2, 2008:2008_1. Source for Foreman Footprint data: Excel File

"Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1", Excel File

"Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B", Excel File

"Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1", Excel File "350 2008_1 compare rev.xlsx" tab "Steve 2008_1 compare rev".

68. The contemporaneous results in the tables above are consistent with my previous findings in the Cantor Class Certification Report, Table 15. For 2006 medical and surgical comparisons, I found that PHCS exceeded the benchmark values 41 to 57 percent of the time for the relevant benchmarks.

69. In summary, my analysis has shown that Dr. Foreman's benchmarks fail to demonstrate a systematic downward bias in the Ingenix Database for medical and surgical procedures. When placed on a contemporaneous basis and using Dr. Foreman's data "as is," comparisons between PHCS percentile values and his benchmarks are consistent with my prior results. The bias results reported by Dr. Foreman depend on his use of lagged values for the PHCS data. By lagging the releases of the Ingenix Database to which he compared his benchmarks, Dr. Foreman inflated his measures of bias and the proportion of comparisons for which Dr. Foreman's benchmark percentile values are purportedly greater than the Ingenix Database percentile values. Inflation in the billed charge values over time is a separate factor introduced by Dr. Foreman into the bias analysis. This factor is not a proper consideration for the investigation of whether there is a systematic downward bias from the alleged data collection and compilation flaws in the Ingenix Database.

D. PHCS Data and Methods Indicate No Obvious Bias

70. My review of the materials available to me indicates that Plaintiffs have not identified any factual evidence or testimony directly supporting their allegations about the “cycle of collusion” and its connection to Ingenix methods. All of the proffered support for Plaintiffs’ allegations that I have reviewed is based on inferences advanced by Plaintiffs’ experts. In this section, I examine information that is contrary to the basic inferences that Plaintiffs’ experts have formed about the data and methods used by Ingenix. My analysis shows that there is substantial supporting information that Ingenix data and methods meet scientific and industry standards for the use and management of large databases.
71. For example, regarding a high-level common sense assessment of Plaintiffs’ allegations, Dr. Foreman testified that one could test for detecting systematic downward bias in the values used by Aetna to evaluate ONET claims:

[I]t would be possible to look at the proportion of claims that appear in the top tier for which billed are greater than allowed. You would expect to see—if these are really truly representative of the 80th percentile, you would expect to see consistently 20 percent of billed less allowed claims in that upper 20th percentile. So that would be a first-level, high-level look at what’s happening with the data.⁵⁶

72. There is evidence that Dr. Foreman’s test has been satisfied in this matter. A declaration provided by Mr. James Laporta of Aetna states, “[f]or the population of claims subject to Ingenix-based fee schedules, approximately 82% of the claims (approximately 14.5 million claims) were allowed at the provider’s full billed charge.”⁵⁷ Mr. Laporta also reports that for the 17,750,237 claim lines subject to Ingenix-based fee schedules, the total allowed amount is approximately 85% of the total billed amount.
73. I also note that Dr. Foreman’s analysis of escalation in Aetna’s billed and allowed charge data over time provides evidence satisfying another test he proposes: “if the process that develops the ‘allowed’ values is ‘neutral’ over time, then billed charge inflation and allowed amounts should generally track one another.”⁵⁸ Although Dr. Foreman omitted the overall inflation result from his table, I have used his data and calculated that billed and allowed charge inflation from 2001 to 2008 was approximately 36 and 42 percent, respectively. Billed inflation is actually less than allowed inflation in the data Dr. Foreman examines. This result satisfies Dr. Foreman’s second test for no downward bias.
74. In the subsections below, I review other information that contradicts Plaintiffs’ maintained hypothesis that the Ingenix Database uses flawed data and methods. My review indicates that Ingenix uses many methods that are found in the management of other large databases published by government and commercial vendors. I also establish that there is little basis to cast suspicions on some of the methods used by Ingenix to manage the large amount of data received by contributors such as organization by

⁵⁶ See Deposition Transcript of Stephen Foreman (the “Foreman Deposition”) (May 17-18, 2010) at p. 71:1-10.

⁵⁷ See Laporta Declaration at ¶ 18.

⁵⁸ See Foreman Report at ¶ 181.

geozips. Finally, I show that whatever the process used by Ingenix, PHCS values are highly consistent with the commercial and government billed charge benchmarks. Plaintiffs' experts have offered nothing but their personal opinions to contradict my analysis showing that these benchmarks represent recognized and reliable but-for values. Information from some of the Association Plaintiffs also supports that the commercial and government benchmarks are recognized reliable sources of billed charge data.

1. Ingenix Procedures Are Common to Manage Large Databases

75. Plaintiffs' experts fail to place the Ingenix Database compilation and construction procedures in the context of industry practices used to manage large databases. Such an assessment is critical for their bias and damage analyses. Information about industry practices addresses directly whether or not such procedures likely would be used but for the "cycle of collusion." My review of automated scrubbing rules for outliers, data pooling, and voluntary contribution of data by contributors indicates that the Ingenix procedures are consistent with industry practice to manage very large databases.
76. For example, the issue of automated data scrubbing has been addressed in peer reviewed literature and professional conferences. As a summary article explains:

It is normally infeasible to guarantee sufficient data quality by manual inspection, especially when data are collected over long periods of time and through multiple generations of database technology. Therefore (semi-) automatic data cleaning methods have to be employed.⁵⁹

77. Automated scrubbing rules for outliers, data pooling, and convenience samples are widely used in compiling and/or maintaining large federal or international databases routinely used in the healthcare industry. Four specific examples are described here; additional examples are contained in Appendix B: Federal and International Data Scrubbing Rules.
78. As an example of automatic scrubbing, the World Health Organization Global Database on Child Growth and Malnutrition uses a rule based on variation in the age data to exclude seemingly inaccurate data. Descriptions of the data quality control methods indicate that survey data that do not conform to expected anthropological patterns are generally excluded from the database.⁶⁰
79. As another example of automatic scrubbing, the Medical Expenditure Panel Survey, which is used to understand healthcare utilization, including price information for visits and prescription drugs, has used automatic editing to adjust price observations that are seemingly inaccurate. Descriptions of the quality control methods indicate an automatic increase for observed retail prices for prescription drugs that are below the average wholesale prices by a specific percentage.⁶¹ This rule not only controls for inaccurate

⁵⁹ See Luebbers D., et al. 2003. "Systematic Development of Data Mining-Based Quality Tools," In Proceedings of the 29th Very Large Data Base Conference, Berlin, Germany at p. 1.

⁶⁰ See de Onis, M. and M. Blossner. 2003. "The World Health Organization Global Database on Child Growth and Malnutrition: Methodology and Applications," International Journal of Epidemiology 2003(32) at p. 519.

⁶¹ See Moeller JF, Stagnitti MN, Horan E, et al. Outpatient Prescription Drugs: Data Collection and Editing in the

data but also for prices that deviate sufficiently from the expected relationship to wholesale prices.

80. As an example of extensive use of data pooling, the Healthcare Cost and Utilization Project's (HCUP) Kids' Inpatient Database (KID) uses post-stratification methods⁶² to pool data according to various characteristics of interest for estimated values. These rules reorganize the data to address the specific issues of the users. For example, the data are organized by broad geographic regions—Northeast, Midwest, West, and South—to capture differences in hospital practices.⁶³
81. In addition to criticisms about scrubbing rules and data pooling, Plaintiffs allege that it is improper to use a convenience sample and to pay participants to collect input data for the Ingenix Database. My review identified that these practices are routinely used in the collection of healthcare data. An important example is the General Practice Research Database (GPRD), which relies on large counts of voluntarily contributed data. It is basically a convenience sample. The database's contributions come from approximately 500 primary care practices in the UK, which serve over 4 million “active patients of research standard.”⁶⁴ The UK-wide dataset covers approximately 8% of the population. In addition, contributors are compensated for their participation.⁶⁵
82. Although a convenience sample, GPRD is a highly regarded data source and is reported to be “the world’s largest computerised database of anonymised longitudinal medical records data from primary care that is linked with other healthcare data.”⁶⁶ The GPRD describes itself as “[t]he most validated of all databases used for drug safety and effectiveness research.”⁶⁷ More than 700 peer-reviewed publications have been generated using the data.⁶⁸ A simple search of PubMed for the keywords “GPRD” or “general practice research database” identified 804 entries.⁶⁹ The website includes a bibliography of papers, presentations, reviews, and other publications using the GPRD.⁷⁰

⁶² 1996 Medical Expenditure Panel Survey (HC-010A), Rockville (MD): Agency for Healthcare Research and Quality; 2001. MEPS Methodology Report 12, AHRQ Pub. No. 01-0002 at p. 12.

⁶³ Post-stratification methods group or weigh data to conform to expected compositions or patterns. See, e.g., Henry, G.T. 1990. *Practical Sampling*. Newbury Park, CA: SAGE Publications at p. 130.

⁶⁴ See Healthcare Cost and Utilization Project, “HCUP Kids’ Inpatient Database Design Report, 1997,” Manual for data collection and editing (Jan. 28, 2002) at p. 2.

⁶⁵ See GPRD, “Welcome to GPRD – The General Practice Research Database,” available at www.gprd.com/home (last visited Oct. 4, 2010) (“GPRD Home”).

⁶⁶ See GPRD, “Contributing Data – FAQ,” available at <http://www.gprd.com/contributing/faqs.asp> (last visited Oct. 4, 2010).

⁶⁷ See GPRD Home (last visited Oct. 4, 2010).

⁶⁸ See GPRD, “The Database,” available at <http://www.gprd.com/products/database.asp> (last visited Oct. 25, 2010) (“GPRD Database”).

⁶⁹ See GPRD Database (last visited Oct. 25, 2010).

⁷⁰ See, e.g., PubMed, “‘GPRD’ OR ‘general practice research database’ – PubMed result,” available at <http://www.ncbi.nlm.nih.gov/pubmed> (last visited Oct. 8, 2010).

2. Geozips and More Aggregate Definitions of Location are Frequently Used to Organize Data

83. Plaintiffs allege that geographic organization of the billed charge data by geozips is a flaw that biases the Ingenix Database. In his report, Dr. Foreman fails to reach a conclusion about the direction of this alleged bias. In the Cantor Expert Report, I reviewed examples of industry practice that indicate a range of approaches to organizing billed charge data geographically. I noted that Wasserman uses the geozip to adjust national reference data to local areas.⁷¹ Recently, FAIR Health reported that it will use geozips to organize the billed charge data.⁷² In this section, I review additional information indicating that even if market-based systems are used to organize some of the billed charge data, they must be supplemented by other definitions—such as geozip or county—to reflect data for the entire U.S. In addition, I illustrate with Dr. Foreman’s example of geozip 601 that reorganization of the data into market-based systems once again simply leads to the “winners and losers” problem that I identified in the Cantor Class Certification Report.
84. There is information that geozips have been used in the healthcare consulting industry to define health markets for pricing data. For example, geozips have been used to measure market-specific provider and facility discounts for major health networks.⁷³ Dr. Foreman has also testified that FAIR Health will be using geozips to organize the billed charge data.⁷⁴
85. Regarding billed charges, geographic areas generally larger than geozips have been used to organize the data. For example, both Medicare and PMIC use the 90 CMS regions. Ms. Hanson of the American Medical Association (“AMA”) testified in her deposition that Mr. Frank Cohen (who performed much of the work on which Dr. Foreman bases his opinions) prefers Metropolitan Statistical Areas (“MSAs”) to organize the data rather than zip codes.⁷⁵
86. MSAs can be larger or smaller than geozips.⁷⁶ For example, the Core Based Statistical Area (“CBSA”) for geozip 601 includes 5 geozips as shown in Figure 1. The 601

⁷¹ See Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2006. *The Original National Dental Advisory Service* 2006. Milwaukee, WI: Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2006 at p. 47.

⁷² See FAIR Health Summary.

⁷³ See, e.g., AONHewitt, “We collect comprehensive discount information on each contract type [...] from every provider in each three-digit ZIP Code where the network is offered. The data is based on actual claims experience...” available at <http://www.hewittassociates.com/Intl/NA/en-US/Consulting/ServiceTool.aspx?cid=5819> (last visited Oct. 21, 2010).

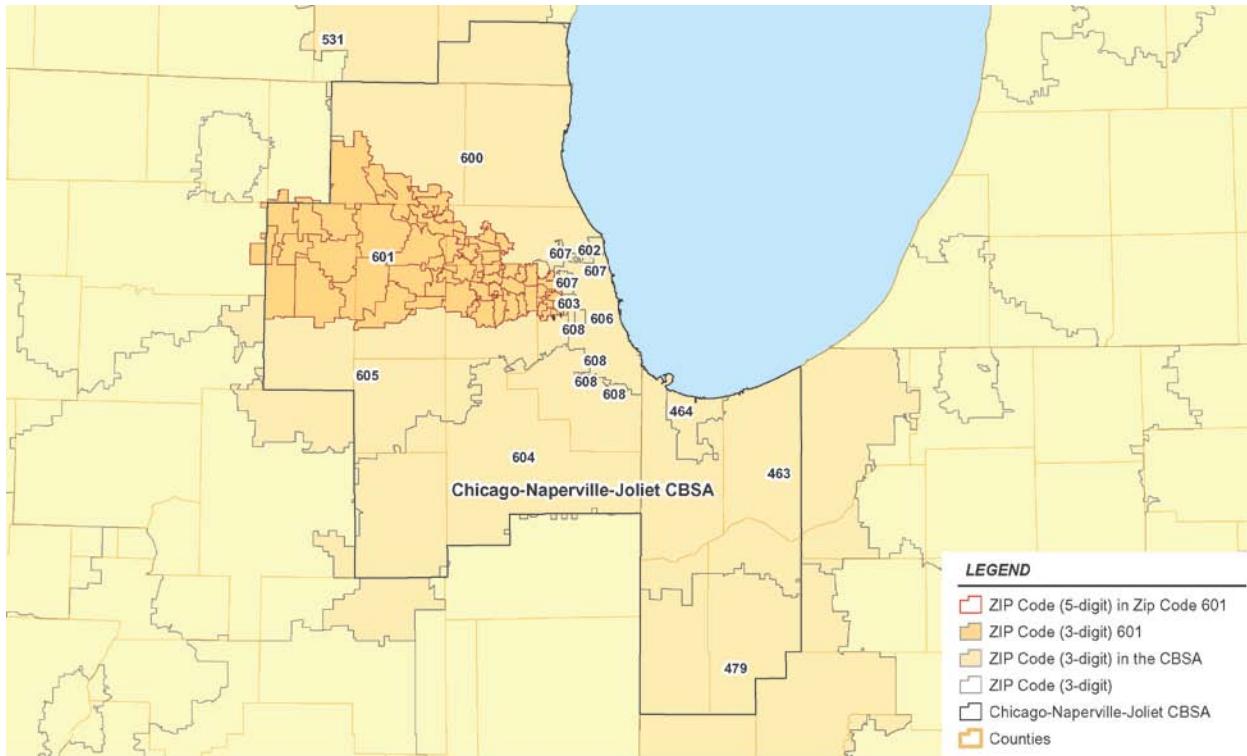
⁷⁴ See Foreman Deposition at pp. 471:23 – 472:15.

⁷⁵ See Deposition Transcript of Catherine Hanson (Jun. 21-22, 2010) (the “Hanson Deposition”) at pp. 298:7-300:3.

⁷⁶ “United States Office of Management and Budget (OMB) defines metropolitan and micropolitan statistical areas according to published standards that are applied to Census Bureau data. The general concept of a metropolitan or micropolitan statistical area is that of a core area containing a substantial population nucleus, together with adjacent communities having a high degree of economic and social integration with that core. [...] The term “core based statistical area” (CBSA) became effective in 2000 and refers collectively to metropolitan and micropolitan statistical areas.” See U.S. Census Bureau, “Metropolitan and Micropolitan Statistical Areas,” available at <http://www.census.gov/population/www/metroareas/aboutmetro.html> (last visited Nov. 3., 2010).

example, selected by Dr. Foreman,⁷⁷ supports my previous findings that additional data pooling or data separation to arrive at some other definition of “community” will affect different members of the purported classes differentially.

Figure 1: Chicago-Naperville-Joliet CBSA



87. Table 11 shows that the CBSA in which geozip 601 resides has a claim-weighted average 80th percentile fee value of \$106 for CPT 99213. If the geographic adjustment were changed from the geozip to the CBSA, services performed in geozip 601 would experience an increase in their average 80th percentile fee value from \$102 to \$106. Services performed in geozip 606, however, would experience a decrease in the same value from \$112 to \$106. I note that in the recent case filed against Blue Cross Blue Shield of Michigan, the U.S. Department of Justice defined Metropolitan Statistical Area, Micropolitan Statistical Area, and collections of counties as relevant geographic markets for the sale of commercial health insurance.⁷⁸ Like geozips, county boundaries are historical constructs that may or may not be related to healthcare market patterns.

⁷⁷ Foreman Report at ¶ 257.

⁷⁸ See Complaint, United States of America and the State of Michigan v. Blue Cross Blue Shield of Michigan (filed Oct. 18, 2010) at ¶ 28.

**Table 11: 80th Percentile Fee Values Vary by Geozip within the Chicago-Naperville-Joliet
CBSA**

Location	80th Percentile
CBSA	\$106.05
Geozip 601	\$102.00
Geozip 606	\$112.00

Notes:

1. Sources for Zip Code data:
Zip-codes.com, ZIP-Codes-Database-deluxe-business.csv, available at www.zip-codes.com (last visited Nov. 9, 2010).
Zip-codes.com, ZIP-Codes-Database-multi-county.csv, available at www.zip-codes.com (last visited Nov. 9, 2010).
Zip-codes.com, C170101.DBF, available at www.zip-codes.com (last visited Nov. 9, 2010), Zip-codes.com, C18101.DBF, available at www.zip-codes.com (last visited Nov. 9, 2010).
Zip-codes.com, C550101.DBF, available at www.zip-codes.com (last visited Nov. 9, 2010).
2. Source for PHCS data: PHCS 2006.

- 88. The analysis of the Chicago-Naperville-Joliet CBSA supports Dr. Foreman's conclusion that the alleged flaw due to the use of geozips is an analysis of "winners and losers".⁷⁹ His analysis failed to demonstrate that this alleged flaw results in a systematic bias downward. Notably, my comparisons to MAG, which attempts to capture market differences for the geographic adjustment factor, failed to show a consistent downward bias.
- 89. State governments provide healthcare fee information organized by definitions that can be broader than geozips, but no less based on data from the postal system. For example, the Maine HealthCost database provides a database with procedure payments for selected procedures state-wide and for insured and uninsured patients. For insured patients, patients can specify their zip code and then they select a radius of interest.⁸⁰ The radii included in the pull-down menu are 10, 25, 50, and 100 miles from the specified zip code.
- 90. As another example, the New Hampshire HealthCost database provides median charges for a limited number of procedures.⁸¹ Users enter their zip code and then select the radius from which they wish to view hospital and provider information. The pre-specified values are 10, 20, and 50 miles and the entire state although users can enter alternate values.
- 91. As another example, the Utah Office of Health Care Statistics allows users to search hospital inpatient discharge data for average and median length of stay and charge information.⁸² The user can select state-wide or specify a county.

⁷⁹ See Foreman Report at ¶ 237.

⁸⁰ See Maine Heath Cost, "Procedure Payments for the Insured," available at http://www.healthweb.maine.gov/claims/healthcost/procedure_pricing_insured.aspx (last visited Oct. 12, 2010).

⁸¹ See NH Health Cost, "Welcome!" available at www.nhhealthcost.org (last visited Oct. 12, 2010).

⁸² See Utah Hospital Discharge Query System, "Descriptive Statistics," available at http://health.utah.gov/hda/hi_iq/hi_iq.html (last visited Oct. 12, 2010).

92. As noted, commercial providers of healthcare data use geozips, but they also use other definitions that can be broader in their geographical coverage. For example, a commercial database, PriceDoc^{TM,⁸³} allows users to select from a variety of services and enter their zip code and desired radius. Users must select the radius from the zip code in which they are interested, that is, no smaller geographic area can be specified. Pre-specified values are 10, 25, and 50 miles from the specified zip code.
93. Economics and other peer-reviewed literature include examples where geozips are used to define markets. As examples, geozips or groupings of geozips have been used to identify rural areas and for sensitivity analysis of other geographical definitions.⁸⁴ Although CBSAs might first seem a likely solution for geographical market definition, as these papers demonstrate, there are gaps in the coverage for the U.S. as a whole. As a result, economics analysis also has relied on geozip or other geopolitical definitions to organize socio-economic data.
94. Based on my review, I continue to find that there is no definitive analysis, and Plaintiffs' experts have offered nothing to the contrary, to reject the use of geozips as a way to organize the billed charge data. In addition, since the Ingenix Database is designed to cover all of the U.S., some form of historically defined organization is necessary to apply to areas such as rural communities that fall outside of recognized CBSAs.

3. PHCS is Highly Correlated with Commercial and Government Benchmarks

95. In my previous expert reports for this matter, I identified and used a number of commercial and government benchmarks for billed charges. No evidence has been revealed to suggest that these benchmarks are affected by the "cycle of collusion" or challenged conduct alleged by Plaintiffs. As a result, in my opinion they continue to be appropriate "yardsticks" to investigate whether the values in the Ingenix Database are systematically biased downward.
96. Nonetheless, Dr. Foreman has suggested that results based on these benchmarks fail to be informative because they have not been tested for reliability "in any way."⁸⁵ I disagree with Dr. Foreman because as an economics matter, these benchmarks are "reviewed" by users in the marketplace for information every day. Dr. Foreman himself has used and endorsed at least one of the commercial benchmarks as "available to all, inexpensive to acquire, totally transparent, unbiased, and geographically sensitive."⁸⁶ In addition, Frank

⁸³ See PriceDoc, "Home," available at www.pricedoc.com (last visited Oct. 12, 2010).

⁸⁴ See e.g. Card, D., et al. 1994. "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania," *The American Economic Review*, Sep. 84(4): pp. 772-793; Card, D., et al. 2000. "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania: Reply," *The American Economic Review*, Dec. 90(5): pp. 1397-1420; Kenney, G., et al. 1991. "Nursing Home Transfers and Mean Length of Stay in the Prospective Payment Era," *Medical Care*, Jul. 29(7): pp. 589-609; Khanna, N., et al. 2000. "Strategic Responses of Incumbents to New Entry: The Effect of Ownership Structure, Capital Structure, and Focus," *The Review of Financial Studies*, Autumn 13(3): pp. 749-779; Robinson, J. 1996. "Administered Pricing and Vertical Integration in the Hospital Industry," *Journal of Law and Economics*, Apr. 39(1): pp. 357-378; Wells, K., et al. 1991. "Mental Health and Selection of Preferred Providers: Experience in Three Employee Groups," *Medical Care*, Sep. 29(9): pp. 911-924.

⁸⁵ See Foreman Responsive Report at ¶ 71.

⁸⁶ See Foreman, S., "An Analysis of the Proposed New Jersey PIP Medical Fee Schedules Physician Fees and

Cohen, who is assisting Dr. Foreman, has endorsed the Medicare PSPS as a benchmark for billed charges.⁸⁷ In the Cantor Report, I identified numerous citations and marketing signals that would be evident to users in the healthcare industry.⁸⁸ My review of these benchmarks indicates that while each might rely on very different data inputs, they all publish values that are highly correlated to Ingenix and to each other. Correlation is a standard statistical measure that is used to demonstrate the relationship between two series of data. A correlation of zero indicates no relationship, and a correlation of one is a perfect relationship. Correlations close to one indicate that the series move together; e.g., high values in one series tend to be associated with high values in the other series. Correlation results are shown in Table 12 for the procedures that comprise the vast majority of Ingenix claims. All correlations exceed 0.9 and some exceed 0.98.⁸⁹

97. As a matter of economics, these correlation results are not surprising because there is a substantial amount of transparent industry data for common procedures. Information from the vendors indicates that the commercial and government benchmarks have access to hundreds of millions of billed-charge observations each year to develop their estimates of percentile values.⁹⁰ Importantly, the correlation results support that my prior results for the matched-pair comparisons between PHCS percentile values and the commercial and government benchmarks were valid comparisons for the investigation of the alleged bias.

Ambulatory Surgery Center Facility Fees," (Dec. 4, 2006) at p. 10.

⁸⁷ See, e.g., American Medical News. 2009. "How to set your fee schedule: Experts advise updating it every 3 to 12 months," available at www.ama-assn.org/amednews/2009/05/04/bisa0504.htm (last visited Oct. 26, 2010).

⁸⁸ See Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the "Cantor Report") at Section 4.C.2.

⁸⁹ Results are qualitatively the same for all Empirical and all Empirical and Derived CPT codes.

⁹⁰ MAG does not provide fee values at percentile levels. MAG reports a Low and High value. I performed several analyses to estimate the percentile value most closely correlated with MAG High fee value. MAG Mutual produced for this matter an Excel file exemplary of the type of data it uses to establish its High and Low values. See Excel File "2010_Final_Fees_Master.xlsx". My staff confirmed with a representative of MAG Mutual that independent contributors supplied data used to establish the MAG High for 2005 and 2006 respectively. I compared the 65th, 75th, 80th, 85th, 90th and 95th percentiles from these data to MAG High. My analysis shows that the 85th and 90th percentiles of these data most closely approximate the MAG High value. These analyses are presented in Appendix C.

Table 12: Benchmark Correlations at CPT Level – Medical/Surgical

Commercial Benchmarks

2006 Top 500 CPTs²		
Comparison	Correlation	
PFR 75th	PMIC 75th	0.953
PFR 90th	PMIC 90th	0.949
PMIC 75th	MAG High	0.969
PMIC 90th	MAG High	0.967
Ingenix 75th	PFR 75th	0.958
Ingenix 75th	PMIC 75th	0.954
Ingenix 85th	MAG High	0.980
Ingenix 90th	PFR 90th	0.958
Ingenix 90th	PMIC 90th	0.953

2007 Top 500 CPTs²		
Comparison	Correlation	
Ingenix 75th	PFR 75th	0.949
Ingenix 90th	PFR 90th	0.946

Notes:

1. Correlations calculated at the CPT level.
2. The "Top 500 CPT Codes" considered here are the top 500 by Ingenix claim count.
3. Source: PHCS 2006 release 2, PHCS 2007 release 2.

Medicare

2006 Top 500 CPTs		
Comparison	Correlation	
Ingenix Mean	Medicare PSPS Mean	0.987

2007 Top 500 CPTs		
Comparison	Correlation	
Ingenix Mean	Medicare PSPS Mean	0.983

Notes:

1. Correlations calculated at the CPT level.
2. The "Top 500 CPT Codes" considered here are the top 500 by Ingenix claim count.
3. Source: PHCS 2006 release 2, PHCS 2007 release 2.

4. The Commercial and Government Benchmarks are Reliable Measures of the But-For Values

a) Use in Peer-Reviewed Analysis

98. In the Cantor Class Certification Report, I presented a review of industry information and websites indicating that the benchmark databases are readily available and routinely referenced in third-party analysis.⁹¹ I also provided a listing of various well-recognized health science journals that published articles relying on the benchmark products.⁹² I did not indicate specifically how the benchmark products were being used. In some cases, the authors referenced data related to Medicare relative value units (RVUs). In others, they used fee values as parts of their analysis. Table 13 is a listing of examples of articles published in well-recognized health science journals that specifically rely on the benchmark products for fee values. In one example, the authors recommend the use of PMIC as a source for obtaining physician fee values:

Because federal antitrust regulations prevent physicians from establishing standards for fees, information on existing fees in any specific geographic area is difficult to obtain. *Common techniques* that a new physician might use include [...] purchasing one of several publications containing ranges for physician fees, such as *Medical Fees in the United States*.⁹³

⁹¹ See Cantor Class Certification Report at Section 4.C.2.

⁹² See Cantor Class Certification Report at p. 15 (Table 3).

⁹³ See Mirkin, D.P., et al. 2000. "Getting Paid in the Managed Care Workplace: The Basics of Physician Compensation," *Hospital Physician*, January: pp. 69-79 (emphasis added).

Table 13: Benchmark Fee Values Used in Peer Reviewed Publications

Year	Article	Benchmark Referenced	Publication
2006	A Multicenter, Retrospective Pilot Study of Resource Use and Costs Associated With Severity of Disease in Glaucoma	PMIC	<i>Arch Ophthalmol.</i> Jan 2006;124(1):12-19
2005	The Cost-Effectiveness of Expanded Testing for Primary HIV Infection	PFR	<i>Ann Fam Med.</i> Sep-Oct 2005;3(5):391-399
2003	Cost-Utility Analysis of Cataract Surgery in the Second Eye	PMIC	<i>Ophthalmology.</i> Dec 2003;110(12):2310-2317
2002	Impact of the Limited Generalist (No Hospital, No Procedures) Model on the Viability of Family Practice Training	MAG/PFR	<i>J Am Board Fam Pract.</i> May-Jun 2002;15(3):191-200
2002	Cost-effectiveness of Gemifloxacin: Results from the GLOBE Study	MAG	<i>Am J Health Syst Pharm.</i> Jul 15 2002;59(14):1357-1365
2001	The Collection of Indirect and Nonmedical Direct Costs (COIN) Form	PFR	<i>Cancer.</i> Feb 15 2001;91(4):841-853
2001	Use of a Decision-Analytic Model to Support the use of a New Oral US Contrast Agent in Patients with Abdominal Pain	MAG	<i>Acad Radiol.</i> Mar 2001;8(3):234-242
2000	Cost for Inpatient Care of Venous Thrombosis: A Trial of Enoxaparin vs Standard Heparin	MAG	<i>Arch Intern Med.</i> Nov 13 2000;160(20):3160-3165
2000	Getting Paid in the Managed Care Workplace: the Basics of Physician Compensation.	PMIC	<i>Hospital Physician.</i> 2000;January 2000:69-79
1999	Cost-Effectiveness of Estimating Gestational Age by Ultrasonography in Down Syndrome Screening	PFR	<i>Obstet Gynecol.</i> Jul 1999;94(1):29-33
1998	The Impact of Candidemia on Length of Hospital Stay, Outcome, and Overall Cost of Illness	MAG	<i>Clin Infect Dis.</i> Oct 1998;27(4):781-788
1995	A Decision Analysis of Practice Patterns Used in Evaluating and Treating Abnormal Pap Smears	PFR	<i>Gynecol Oncol.</i> Oct 1995;59(1):75-80

b) Use by Industry and Practitioners

99. There is information that indicates that the commercial products are not only recognized as benchmarks in the industry but also used by industry associations in their agreements with insurers as well as by Aetna. For examples, PFR was used by the Physicians Medical Group of San Jose as part of a claim delegation agreement with Aetna and MAG was used for such purposes with the Marin IPA.⁹⁴

⁹⁴ See, e.g. AET-03582589-98 and AET-035822477-86. The San Jose group's website reports that it contains 380 physician members. See Physicians Medical Group of San Jose, "About Us," available at <http://www.pmgmd.com/aboutus.htm> (last visited Nov. 3, 2010). The Marin group's website reports that it contains 300 members. See Marin IPA, "Welcome to Marin County's Health Care Network," available at <http://www.marinipa.com/members.asp> (last visited Nov. 3, 2010).

100. I have noted previously that the AMA advertises on its web site that it sells the MAG Mutual Physician Fee & Coding Guide. Ms. Hanson, who testified as a representative of the AMA stated that such placement goes through a vetting process by the AMA before a product is posted.⁹⁵ The AMA “sell sheet” that is used to describe the MAG product states that it is from “one of the leading sources on physician fees charged to commercial carriers (or private insurers)” and a “reliable source.”⁹⁶
101. In addition, employees of the named Association Plaintiffs have provided deposition testimony and documents indicating that they are aware of the benchmark products that I use in my analysis. This information also indicates that some associations provide information about the benchmarks to members in the context of setting fees.
102. Matthew Katz of the Connecticut State Medical Society testified that he has knowledge of several of the commercial benchmark products including MAG, PMIC, and PFR, as well as Medicare PSPS.⁹⁷ In his deposition, Mr. Lee Spangler of the Texas Medical Association (“TMA”) verified a document listing benchmarking products that TMA personnel use to answer questions posed by member physicians about setting fees.⁹⁸ This document includes references to Wasserman (PFR), MAG, and PMIC products to “help guide physicians in the area of fee structuring.”⁹⁹ Similarly, Jeff Scott of the Florida Medical Association (“FMA”) testified that the Wasserman Physician’s Fee Reference (PFR) is identified by FMA as a reference source in their publication FMA Legal Doctor.¹⁰⁰ The document is titled “Establishing A Physician Fee Schedule.”¹⁰¹ In addition, a chapter entitled, *Building a Defensible Fee Schedule: An Analytical Approach to Establishing and Maintaining Charges* of a manual on best practices published by the California State Medical Association includes a section on benchmarking fees.¹⁰² The document explains that “[a] benchmark is standard against which something can be measured or judged...it is acceptable for a practice to benchmark its fees against an external set of standards.”¹⁰³ The document describes Medicare PSPS as “an excellent data source to determine average charge levels.”¹⁰⁴
103. This information further confirms my prior conclusions that the commercial and government benchmark are known to the healthcare industry and are regarded as easily accessible and reliable sources of billed charge data. Plaintiffs’ experts have not contradicted this view and therefore have not altered my conclusion that the commercial and government benchmarks are the proper yardsticks for investigating the alleged downward bias of the values in the Ingenix database. As I demonstrated in my prior reports, which I incorporate by reference in this report, these independent benchmarks

⁹⁵ See Hanson Deposition at pp. 315:3-316:2 and.

⁹⁶ See AMA-AET-50945 (emphasis in the original).

⁹⁷ See Deposition Transcript of Matthew Katz (Jul. 9, 2010) (the “Katz Deposition”) at pp. 158:6-14, 161:4-17, 166:25-167:4, 170:24-171:4, and 173:7-15.

⁹⁸ See Deposition Transcript of Lee Spangler (Jul. 22, 2010) at pp. 165:19-166:16 and TMA-AET-08111

⁹⁹ See TMA-AET-08111

¹⁰⁰ See Deposition Transcript of Jeff Scott (Jul. 27, 2010) at pp. 160:8-22; 162:8-163:5.

¹⁰¹ See FMA-AET-00278.

¹⁰² See CMA 6. I note that this chapter was written by Mr. Frank Cohen who has assisted Dr. Foreman in this matter.

¹⁰³ Ibid at p. 78.

¹⁰⁴ Ibid at p. 78.

undermine any claim that the percentile values in the Ingenix Database are biased downward on either an across-the-board or average basis.

c) Legal/Regulatory Use

104. In addition, there is other information that indicates that Medicare is a recognized standard in state legal and regulatory proceedings.¹⁰⁵ States are responsible for the maintenance of medical fee schedules for several programs, including Medicaid, Workers' Compensation and, in some states, Personal Injury Protection. In many cases, states benchmark to Medicare values to establish these fees. While this is not without controversy, it is an area that receives substantial review, challenge, and adjustment, suggesting that the Medicare benchmark is still regarded as an appropriate benchmark for such purposes.
105. For example, 12 states (Florida, Hawaii, Kansas, Kentucky, Massachusetts, Michigan, Minnesota, New Jersey, New York, North Dakota, Pennsylvania and Utah) have compulsory "no-fault" insurance, while other states offer no-fault and traditional insurance.¹⁰⁶ Coverage for the policyholder is referred to as personal injury protection. These states use a variety of systems for determining payment that includes linking to the Medicare Fee Schedule or using Medicare's Resource-Based Relative Value Scale ("RBRVS"), adjusted for geography.¹⁰⁷
106. Workers Compensation fee schedules, used by 43 states, are also sometimes tied to the Medicare Fee schedule. Obviously, these fee schedules are intended to apply to procedures for workers who are not a Medicare population, and some states adjust the values accordingly. For example, Tennessee's Workers' Compensation Medical Fee Schedule documentation states that "when there is no specific methodology in these Rules for reimbursement, the maximum reimbursement is 100% of Medicare."¹⁰⁸ Hawaii's Workers' Compensation Medical Fee Schedule maximum values are 100% of the Medicare reimbursement.¹⁰⁹ Maryland ties its Workers' Compensation schedule to Medicare using a Maryland Specific Conversion Factor.¹¹⁰ Arkansas' and Minnesota's

¹⁰⁵ See In Re Adoption of N.J.A.C. 11:3-29 by the State of New Jersey, Department of Banking and Insurance, No. A-0344-07T3 (N.J. Super. Ct. App. Div. filed Aug. 10, 2009).

¹⁰⁶ See Insurance Information Institute, "No-Fault Auto Insurance," available at <http://www.iii.org/media/hottopics/insurance/nofault/> (last visited Nov. 1, 2010).

¹⁰⁷ See e.g., State of Florida, "627.551 Group contracts and plans of self-insurance must meet group requirements," available at http://www.leg.state.fl.us/statutes/index.cfm?App_mode=Display_Statute&Search_String=&URL=0600-0699/0627/Sections/0627.551.html (last visited Oct. 20, 2010); State of Hawaii, "Hawaii Administrative Rules §16-23-93," available at http://hawaii.gov/dcca/ins/har/har_23-c.pdf (last visited Oct. 21, 2010); See State of Utah, "Insurance Department, Bulletin 2010-1," available at <http://www.insurance.utah.gov/docs/bulletins/2010-1Signed.pdf> (last visited Oct. 19, 2010); See State of Utah, "Utah Code §31A-22-307" available at http://le.utah.gov/~code/TITLE31A/htm/31A22_030700.htm (last visited Oct. 21, 2010).

¹⁰⁸ See Tennessee's Workers' Compensation Medical Fee Schedule, "General Information, p.6" available at http://www.state.tn.us/labor-wfd/wc_medfeebook.pdf (last visited Oct. 14, 2010).

¹⁰⁹ See Legislative Reference Bureau, State of Hawaii, "The Medical Fee Schedule Under The Workers' Compensation Law," available at <http://hawaii.gov/lrb/rpts98/fee.pdf> (last visited Oct. 14, 2010).

¹¹⁰ See Maryland Workers' Compensation Commission, "This is the Maryland Workers' Compensation Commission Medical Fee Guide Maryland Specific Conversion Factor (MSCF)/Multiplier (COMAR 14.09.03)" available at http://www.wcc.state.md.us/PDF/MFG/MSCF_rate.pdf (last visited Oct. 14, 2010).

Workers' Compensation Medical Fee Schedules are linked to CMS RBRVS values.¹¹¹ Recent research exploring workers' compensation reimbursement levels also uses Medicare as a comparative benchmark.¹¹²

E. Plaintiffs' Experts Proffer No Reliable Foundation for Their Choice of "But For" Benchmarks

107. In their previous reports, Plaintiffs' experts argue for multiple reasons that the available commercial and government benchmarks used in my analysis of bias are inappropriate for this purpose. However, they have not presented a viable alternative, nor have they attempted to prove their assertions that the commercial benchmarks are scientifically unsound. None of Plaintiffs' experts have identified information or testimony to demonstrate that the commercial and government benchmarks are flawed and should not be the obvious choices for the but-for benchmarks. Plaintiffs' experts improperly have ignored that if the commercial and government benchmarks are flawed in the same ways as the Ingenix Database, then how can the flaws be the "end result of this cycle of collusion"? Notwithstanding their failure to address this issue, Plaintiffs' experts have opined on the standards that should be met for a source of billed charge data to be used as a benchmark for the Ingenix Database.
108. Specifically, in his responsive report, Dr. Siskin makes the following arguments. First, since the Ingenix Database does not report distributions by qualification, training or experience, comparison to PFR cannot address these issues. Second, without "detailed knowledge" of the PFR data collection, editing and processing techniques studies done with the PFR data cannot be given meaning:

PHCS does not report distributions by the qualifications, training or experience of the provider or by type or location of service. If PFR does so, then it is not clear how Dr. Slottje is making his comparisons. If they do not do so, then Dr. Slottje's study does not address any of these concerns. Moreover, without detailed knowledge of the data collection and tabulation methodology, one cannot determine if the PFR data has the same methodological issues in data collection and editing of data.¹¹³
109. In his responsive report, Dr. Foreman devotes a great deal of attention to the analysis involving the five commercial benchmarks. Dr. Foreman asserts that the commercial benchmarks are subject to the same alleged problems as the Ingenix Database, are not UCR, and are not comparable to the Ingenix data.¹¹⁴ Despite these opinions, Plaintiffs'

¹¹¹ See Arkansas Workers' Compensation Commission, "Medical Fee Schedule," available at <http://www.awcc.state.ar.us/rule30misc/newmedfeesch.html> (last visited Oct. 22, 2010); Minnesota Department of Labor and Industry, "Background about the relative value for fee schedule," available at http://www.dli.mn.gov/WC/PDF/RVU_background.pdf (last visited Oct. 14, 2010).

¹¹² See, e.g., Workers Compensation Research Institute, "Abstracts: Benchmarks for Designing Workers' Compensation Medical Fee Schedules: 2009," available at http://www.wcrinet.org/studies/public/abstracts/fee_sched_09-ab.html (last visited Oct. 22, 2010).

¹¹³ See Report in the Matter of Aetna UCR Litigation by Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 30, 2010) at pp.1-2.

¹¹⁴ See Foreman Responsive Class Certification Report at ¶¶ 47-49. I note that Dr. Foreman conducts no analysis of

experts sponsor two benchmark databases that fail to solve the alleged flaws and have no independent evidence of their validity. Plaintiffs' experts have neither attempted to offer a proof that Dr. Foreman's benchmarks satisfy the criteria they have advanced for the but-for data, nor have they demonstrated that Dr. Foreman's data are "internally accurate." I examine in the sections below why Dr. Foreman's benchmarks are unreliable surrogates for the data that would exist but for the use of Ingenix methods or in a world absent the alleged "cycle of collusion."

1. Dr. Foreman's Benchmarks Fail to Overcome the Flaws Alleged by Plaintiffs

110. I have found that the benchmark products discussed in my prior reports exhibit exactly the kind of qualities one looks for in yardstick data for calculating damages. They are consistent with one another, used in peer-reviewed and published articles, known and used by medical associations (including some named Association Plaintiffs), used by insurance companies as alternatives to the Ingenix Database, used as the foundation for state fee schedules, developed independently of the Defendants, and are free of the challenged conduct.
111. In contrast, Dr. Foreman's benchmarks are not commercial or readily available products. They have not been tested in the marketplace or compared to data from field studies. They have not been used directly by insurance companies or physicians. Based upon the production materials submitted by Dr. Foreman, I cannot verify whether his benchmarks have been constructed in accordance with any recognized or peer-reviewed methodology. Dr. Foreman's supposedly "accurate percentile" values provide substantial evidence to the contrary because they frequently do not even match each other (or come anywhere close to each other) for the same CPT code, geographic area, and time period in his two studies. In fact, there are nonsensical values in his benchmarks, which I discussed above, that no informed data manager or user had the opportunity to identify.
112. As measures of the "internally accurate percentile" values, Dr. Foreman's benchmarks also fail. Dr. Foreman recognizes that his benchmarks do not correct the alleged flaw of representativeness.¹¹⁵ In addition, Dr. Foreman's benchmarks do not correct the alleged data scrubbing flaw because he fails to distinguish between outliers and truly fraudulent or miscoded data. Dr. Foreman has not reported any methodology for ensuring that his changes from Ingenix's processes have not introduced new errors to his benchmarks, such as by altering processes that are not challenged by Plaintiffs as improper. His benchmarks do not correct for provider specialties because the contributor data generally lack these details about the provider.¹¹⁶ They do not correct for place of service, although the contributor data generally do contain this information. As I have noted, Dr. Foreman's solution for modifiers is to "drop all claims with modifiers in constructing

his own to verify these claims.

¹¹⁵ See Foreman Report at ¶¶ 277, 380, 389, 393, 394, 446, 447.

¹¹⁶ Dr. Foreman discusses, but does not offer any analysis of these alleged flaws. In Appendix A, I provide an analysis of the specialty and place of service facts that indicates these alleged flaws tend to increase the billed charge values. Once again, there is information that Plaintiffs' experts have ignored which is contrary to the unsupported impressions that data pooling leads to a systematic downward bias.

the percentile values.”¹¹⁷ They do not control flaws in the methods used to construct derived data because no such combinations are examined. They do not correct the influence of geozips as the geographical reference for the data because Dr. Foreman organizes his data by geozips. In sum, Dr. Foreman has provided no analysis to indicate how close or far his benchmarks are from the desired “internally accurate” standard, but it is a virtual certainty that his benchmarks are not that standard.

2. Dr. Foreman’s Benchmarks Are Not Representative of the But-For Billed Charges

113. Dr. Foreman’s approach to constructing benchmarks for measuring the alleged bias in the Ingenix Database basically is to select subsets of the contributor data and ignore large numbers of procedure/geozip combinations. For his 300 Study, Dr. Foreman attempts to justify this approach by an appeal to large numbers: “[t]he 90,000 combinations used half of the contributor data in 2006, 56% in 2007 and 65% in 2008.”¹¹⁸ Coverage of the contributor claim data, however, does not guarantee adequate coverage of the Ingenix Database combinations or the population of combinations relevant to the subject Aetna data. Dr. Foreman is measuring the alleged percentile bias at the level of the procedure/geozip *combination*. Although he derives a claim-weighted bias estimate, this calculation in no way resolves the representativeness issue that his sample raises. He is extrapolating his results to millions of combinations that he never examines and for which he has proffered no methodology to infer an equivalent estimate of the alleged bias. Dr. Foreman reports no investigations that address these coverage issues or the implications for his bias and damages analyses.
114. Importantly, Dr. Foreman’s benchmarks are not random samples of the procedure/geozip combinations present in the contributor data, but rather they reflect specific “footprints” of the available combinations.¹¹⁹ To construct his 300 Study benchmark, Dr. Foreman selected “the 300 most common procedure codes in 300 geozip areas selected at random.”¹²⁰ Although these approximately 90,000 CPT/geozip combinations apparently reflect more than half of the contributor data, Dr. Foreman’s selected “footprint” is actually a fraction of the procedure/geozip combinations available to him. Regarding all procedure/geozip combinations, excluding anesthesia, Dr. Foreman’s 300 Study only contains less than one percent of the possible combinations to be examined in the Ingenix Database from 2006 to 2008. This is shown in Table 14.

¹¹⁷ See Foreman Report at ¶ 295. I note that Dr. Foreman fails to conclude that modifiers cause the PHCS percentile values to be biased downward. Ignoring this result, he removes all contributor data with modifiers from the construction of his benchmarks. This is an arbitrary decision and Dr. Foreman provided no investigation of its implication for his subsequent analysis of overall bias. In the absence of a sound basis to remove the modifier data, Dr. Foreman should have conducted a sensitivity analysis of his arbitrary decision.

¹¹⁸ See Foreman Report at ¶ 289. I note that Dr. Foreman’s reported proportions do not match the percentages given in his supporting table.

¹¹⁹ In his deposition, Dr. Foreman acknowledged that his 300 Study is not a random sample. See Foreman Merits Deposition Volume I at pp. 112:21-113:6.

¹²⁰ See Foreman Report at ¶ 288. Dr. Foreman’s production suggests that the 300 geozips were not selected randomly. He confirms this finding during his deposition (See Foreman Merits Deposition Volume I at pp.113:9-114:6).

Table 14: Proportion of PHCS Procedure Code/Geozip Combinations Covered by Foreman's 300 Footprint – All System Codes Excluding Anesthesia, 2006-2008

Year	Match	Combination Count	Combination Share	PHCS Claim Count	PHCS Claim Share
2006	Inside 300 CPT Footprint	83,451	0.7%	436,401,808	37.2%
	Outside 300 CPT Footprint	11,898,061	99.3%	735,737,981	62.8%
2007	Inside 300 CPT Footprint	91,575	0.8%	571,383,070	44.9%
	Outside 300 CPT Footprint	11,781,904	99.2%	700,550,876	55.1%
2008	Inside 300 CPT Footprint	95,409	0.8%	624,400,905	46.8%
	Outside 300 CPT Footprint	11,949,194	99.2%	709,940,002	53.2%
Overall					
2006-2008	Inside 300 CPT Footprint	270,435	0.8%	1,632,185,784	43.2%
	Outside 300 CPT Footprint	35,629,159	99.2%	2,146,228,858	56.8%

Notes:

1. PHCS is defined here as all files, all system codes excluding Anesthesia.
2. Foreman data includes all procedure codes produced for medical/surgical, dental and HCPCS.
3. These comparisons are contemporaneous between the data published in PHCS and the data produced by Dr. Foreman.
4. Source for data: Foreman Footprint data - Excel File "Compare 300 CPT 2006_2.xlsx" tab "Ing 2006 v1", Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07" and Excel File "Comp 300 Ing 08 rev.xlsx" tab "2007med". PHCS Data - PHCS 2006 release 2, PHCS 2007 release 2, PHCS 2008 release 1.

115. In my prior analysis of the alleged bias in the 2006 Ingenix Database, I examined more than 6000 CPT and CDT codes, and approximately 1.4 million procedure/geozip combinations. Although my analysis addressed all empirical and ultimately all derived procedure/geozip combinations in the medical and surgical combinations, Dr. Foreman's 300 Study is only capable of covering approximately 5 percent of the subject empirical combinations, and zero percent of the derived combinations. In addition, Dr. Foreman's 300 Study is only capable of covering approximately 6 to 7 percent of the dental combinations. The combination counts and shares of the number of empirical combinations in PHCS are shown in Tables 15 and 16.

Table 15: Proportion of PHCS CPT/Geozip Combinations Covered by Foreman's 300 & 350 Footprints – Medical/Surgical, Empirical Only

Contributor	PHCS Release	Foreman 300 Combinations ¹	Foreman 350 Combinations ²	PHCS Combinations ³	Foreman 300 Proportion of CPT/Geozip Combinations	Foreman 350 Proportion of CPT/Geozip Combinations
Year						
2006	2005.2	62,086	67,412	1,280,979	4.8%	5.3%
	2006.1	62,086	68,516	1,206,901	5.1%	5.7%
2007	2006.2	59,769	46,404	1,323,720	4.5%	3.5%
	2007.1	63,812	51,106	1,304,927	4.9%	3.9%
2008	2007.2	63,825	103,030	1,284,589	5.0%	8.0%
	2008.1	66,219	108,061	1,219,307	5.4%	8.9%

Notes:

1. Source: Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 20.

2. Source: Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 25.

3. Source: Ingenix PHCS Releases 2005.2, 2006.1, 2006.2, 2007.1, 2007.2, 2008.1. Included are CPT codes for Medical, Surgical Radiology total, and Pathology/Lab total.

Table 16: Proportion of PHCS CDT/Geozip Combinations Covered by Foreman's 300 Footprint

Contributor	PHCS Release	Foreman 300 Combinations ¹	PHCS Combinations ²	Foreman 300 Proportion of CDT/Geozip Combinations
Year				
2006	2005.2	11,558	157,993	7.3%
	2006.1	0	168,399	0%
2007	2006.2	0	170,742	0%
	2007.1	10,661	165,547	6.4%
2008	2007.2	10,661	165,560	6.4%
	2008.1	11,065	172,251	6.4%

Notes:

1. Source: Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 21.

2. Source: PHCS Releases 2005.2, 2006.1, 2006.2, 2007.1, 2007.2, 2008.1. Included are CDT codes with a record type of "30".

116. The table above also shows that Dr. Foreman's second benchmark for the 350 Study is no less selective and no less anemic in its coverage of the Ingenix Database than his first. He states that "[i]t included the 350 most common 350 [sic] codes since they represent 90% of the claims lines and 450 most common geozips with the most claims since these geozips represent 90% of the claims."¹²¹ Dr. Foreman's benchmark, however, generally is the intersection of these CPTs and geozips and because of his selection methods, many procedure/geozip combinations are dropped.¹²² The 350 Study's coverage of the Ingenix

¹²¹ See Foreman Report at ¶ 290.

¹²² For example, my review of Dr. Foreman's "final" 2007 dataset which he compared to PHSC 2006 release 2

Database is far more modest than the approximately 158,000 combinations implied by the intersection of 350 procedures for 450 geozips. Depending on the time period, the table above shows that the 350 Study contains approximately 46,000 to 108,000 medical and surgical combinations.¹²³ Although Dr. Foreman claims to be using 90 percent of the claims in his analysis of the alleged bias, his results for 2007 only cover approximately 55 percent of the PHCS claims as shown in Table 17 and approximately 4 percent of the available combinations as shown in the last column of Table 15. The 350 Study contains no dental combinations at all.

Table 17: Proportion of PHCS Claim Count Covered by Foreman's 300 & 350 Footprint – Medical/Surgical

Contributor Year	PHCS Release	Foreman 300 Claim Count ^{1,4}	Foreman 350 Claim Count ^{2,4,5}	PHCS Claim Count ³	Foreman 300 Proportion of Claim Count	Foreman 350 Proportion of Claim Count
2006	2005.2	347,470,109	374,489,064	644,160,393	53.9%	58.1%
	2006.1	306,885,063	358,748,960	574,654,857	53.4%	62.4%
2007	2006.2	396,093,573	392,720,579	713,012,637	55.6%	55.1%
	2007.1	440,629,063	-	747,126,935	59.0%	-
2008	2007.2	449,538,442	516,583,753	750,298,957	59.9%	68.9%
	2008.1	476,695,700	557,825,860	780,248,960	61.1%	71.5%

Notes:

1. Sources used to establish 300 Footprint: 2006 - Excel File "Compare 300 CPT 2006_2.xlsx" tabs "Ing 2005 v2" & "Ing 2006 v1"; 2007 - Excel File "Comp 300 Ing_07_02 Rev.xlsx" tabs "medsurg06" & "medsurg07"; 2008 - Excel File "Comp 300 Ing 08 rev.xlsx" tab "2007med", Excel File "Comp 300 Ing _08_08 Rev.xlsx" tab "MEDSURG".
2. Sources used to establish 350 Footprint: 2006 - Excel File "Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1", Excel File "Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B"; 2007 - Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1"; 2008 - Excel File "350 2008_1 compare rev.xlsx" tab "Steve 2008_1 compare rev", Excel File "350 2008_2 Compare Rev.xlsx" tab "Steve 2008_2 Compare Rev" .
3. Source for PHCS data: PHCS Releases 2005.2, 2006.1, 2006.2, 2007.1, 2007.2, 2008.1. Included are CPT codes for Medical, Surgical Radiology total, and Pathology/Lab total.
4. Foreman 300 Claim Count and Foreman 350 Claim Count refer to the PHCS claim count within the appropriate Foreman footprint.
5. A 350 Study 2007.1 source file was does not appear to have been produced by Dr. Foreman and so the Footprint for this PHCS release cannot be determined.

117. The coverage results in the above tables also reflect Dr. Foreman's decision not to examine all of the combinations he theoretically selected in his definition of the footprints. Among other factors, he indicates that he eliminated all claims with modifiers and all combinations with fewer than 255 contributor claims.¹²⁴ In addition, for the 350 Study Dr. Foreman seems to have examined only the first geozip in a geozip batch record (a record applying to two or more geozips) as I discussed in section B.3, which

indicates that not a single one of his 450 "most common" geozips contain data for all 350 "most common" CPTs that he purports to use for his benchmarks.

¹²³ I understand that the approximately 108,000 combinations are a result of a change in Dr. Foreman's methodology. With insufficient explanation, he used all geozips for his 2008 data. See Foreman Report at note 96.

¹²⁴ See Foreman Report at ¶ 297. In a subsequent section, I note that Fair Health will estimate percentile values with samples of 40 claims or more. Dr. Foreman's limitation to 255 or more claims apparently is due to his use of the sample size requirements for estimating a proportion—not the sampling problem at issue here.

apparently caused his benchmark to drop large numbers of procedure/geozip combinations.

118. The restriction that the procedure/geozip combination had to contain 255 claims or more causes only 4.3 percent of the combinations in the Ingenix medical and surgical modules to be relevant at all for Dr. Foreman's selection methodology. This is shown in the last row of Table 18 which indicates the share of combinations in groups defined by the claim count in the combination. Although Dr. Foreman bases his analysis on benchmarks containing approximately 60,000 to 80,000 procedure/geozip combinations, there are approximately 300,000 combinations annually in PHCS with more than 255 claims—Dr. Foreman's only focus—and another approximately 400,000 combinations that have between 40 and 254 claims.

**Table 18: Share of PHCS CPT/Geozip Combinations by Claim Count Groups
Medical/Surgical, Empirical & Derived**

Year	CPT/Geozip Grouping	Count	Share
2006	Less than 9 Claims	6,091,614	82.1%
	9 to 39 Claims	564,904	7.6%
	40 to 254 Claims	434,452	5.9%
	More than 255 Claims	324,364	4.4%
2007	Less than 9 Claims	6,174,397	82.8%
	9 to 39 Claims	546,629	7.3%
	40 to 254 Claims	419,229	5.6%
	More than 255 Claims	318,731	4.3%
2008	Less than 9 Claims	6,244,463	83.7%
	9 to 39 Claims	516,293	6.9%
	40 to 254 Claims	395,575	5.3%
	More than 255 Claims	307,439	4.1%
Overall			
2006-2008	Less than 9 Claims	18,510,474	82.9%
	9 to 39 Claims	1,627,826	7.3%
	40 to 254 Claims	1,249,256	5.6%
	More than 255 Claims	950,534	4.3%

Notes:

1. Source: PHCS 2006 release 2, PHCS 2007 release 2, PHCS 2008 release 1.

119. Due to his selective approach, the combinations in Dr. Foreman's 300 Study, which is the foundation for his measure of bias used in his damages calculations, are applicable to a mere 19 percent and 12 percent of the subject Aetna medical/surgical and dental procedure/geozip combinations, respectively. The shares of claims and combinations are shown in Table 19 for medical and surgical procedures and Table 20 for dental procedures. The tables also indicate the share of Aetna claims that fall into the combinations inside and outside of Dr. Foreman's footprints. Dr. Foreman's benchmarks can yield no direct results for approximately 35 to 46 percent of the subject Aetna claims.¹²⁵ In contrast, data for all or nearly all medical, surgical and dental procedures

¹²⁵ In fact, the proportion of claims not addressed directly by Dr. Foreman's analysis is larger than these percentages imply since he extrapolates his results to claims with modifiers although he did not examine such claims.

by various geographic references are available in the commercial benchmarks for comparison to PHCS and the analysis of the alleged bias relevant to the subject Aetna claims.¹²⁶

Table 19: Proportion of ACAS CPT/Geozip Combinations Covered by Foreman's 300 Footprint – Medical/Surgical, 2006-2008

Year	Match	Combination Count	Combination Share	Claim Count	Claim Share
2006	Inside 300 CPT Footprint	27,104	17.9%	1,012,587	54.3%
	Outside 300 CPT Footprint	124,534	82.1%	850,703	45.7%
2007	Inside 300 CPT Footprint	28,087	19.5%	1,054,346	57.7%
	Outside 300 CPT Footprint	116,218	80.5%	771,381	42.3%
2008	Inside 300 CPT Footprint	27,393	20.6%	1,067,828	59.2%
	Outside 300 CPT Footprint	105,539	79.4%	734,510	40.8%
Overall					
2006-2008	Inside 300 CPT Footprint	82,584	19.3%	3,134,761	57.1%
	Outside 300 CPT Footprint	346,291	80.7%	2,356,594	42.9%

Notes:

1. ACAS Data sourced from: Excel File "Aetna2006 Medical Damaged Claims.csv", Excel File "Aetna2007 Medical Damaged Claims.csv", Excel File "Aetna2008 Medical Damaged Claims.csv".

2. Foreman data sourced from : Excel File "Compare 300 CPT 2006_2.xlsx" tab "Ing 2006 v1", Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07", Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "MEDSURG".

¹²⁶ The commercial benchmarks cover 99 percent and 99.3 percent of the medical/surgical and dental ACAS claims, respectively. The commercial benchmarks cover 97.3 percent and 98.6 percent of the medical/surgical and dental P3HCS claims, respectively.

Table 20: Proportion of ACAS CDT/Geozip Combinations Covered by Foreman's 300 Footprint – 2006-2008

Year	Match	Combination Count	Combination Share	Claim Count	Claim Share
2006	Inside 300 CDT Footprint	10,886	12.2%	3,583,175	59.8%
	Outside 300 CDT Footprint	78,099	87.8%	2,411,674	40.2%
2007	Inside 300 CDT Footprint	10,230	11.4%	3,920,857	64.2%
	Outside 300 CDT Footprint	79,783	88.6%	2,187,641	35.8%
2008	Inside 300 CDT Footprint	10,621	11.8%	3,920,469	65.3%
	Outside 300 CDT Footprint	79,498	88.2%	2,085,877	34.7%
Overall					
2006-2008	Inside 300 CDT Footprint	31,737	11.8%	11,424,501	63.1%
	Outside 300 CDT Footprint	237,380	88.2%	6,685,192	36.9%

Notes:

1. ACAS Data sourced from: Excel File "Aetna2006 Dental Damaged Claims.csv", Excel File "Aetna2007 Dental Damaged Claims.csv", Excel File "Aetna2008 Dental Damaged Claims.csv".
2. Foreman data sourced from : Excel File "Ingenix 2006 contributor versus published for top 300 Codes in top 300 GeoAreas.xlsx" tab "2006 Contributor", Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "dental07", Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "DENTAL".
3. Values for 2006 were calculated using the Excel File "Ingenix 2006 contributor versus published for top 300 Codes in top 300 GeoAreas.xlsx" produced by Dr. Foreman in the instant matter as noted above. In "Table 21" of his Expert Merits report, Dr. Foreman states that he uses 11,558 CDT/geozip combinations in his comparison of the dental data found in the 2006 contributor data to the second PHCS release of 2005. By removing CDT/geozip combinations from the above-cited Excel File that have "Null" Ingenix values or contributor percentiles less than \$1, we arrive at 11,558 CDT/geozip combinations. This set of combinations has been used to compute the 2006 values. See Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 19.

120. In addition, Dr. Foreman's selective approach to construct his benchmarks leads to important geographical gaps in his data. My review of files produced by Dr. Foreman indicates that he failed to include data for five states in his 300 Study benchmarks—these states were Hawaii, Idaho, Maine, Vermont, and South Dakota in 2006 and Hawaii, Maine, Montana, Vermont, and South Dakota in 2007 and 2008. He also failed to include four states in his 350 Study benchmark in the years 2006 and 2007—Hawaii, Nevada, West Virginia, and Wyoming.
121. My review of these files also indicates that Dr. Foreman failed to include in his benchmarks many procedure/geozip combinations that have high dollar amounts but relatively lower claim counts. Both Dr. Foreman and Dr. Rausser have opined about the alleged bias in high-price procedures. Table 21 shows that the average 80th percentile values from the Ingenix Database outside of Dr. Foreman's 300 and 350 Studies' footprints are generally substantially higher than the averages in his footprints. For example, the first row shows that inside Dr. Foreman's footprint, the average 80th percentile value for PHCS is \$107.95. Outside the footprint—and therefore ignored by Dr. Foreman—the average Ingenix 80th percentile value is \$161.58. This flaw in his representativeness might inflate the measure of downward bias by dollar spent and I show below that the revenue-weighted results do indeed reflect this bias. Failing to properly account for the high price/low frequency procedures is less evident with Dr.

Foreman's claim-weighted results. Nonetheless, my analysis demonstrates that results based on Dr. Foreman's footprints might not apply to compositions of ONET claims with higher proportions of high price/low frequency procedure/geozip combinations.

Table 21: Average 80th Percentile Fee Comparison, Foreman Footprint Procedure Codes v. "Outside" of Footprint Codes

Foreman Footprint ¹	Comparison ²	Foreman Contributor		PHCS Average 80th in Footprint ¹	PHCS Average 80th Outside Footprint ¹	PHCS Average 80th - All Empirical CPTs	PHCS Average 80th - All Empirical & Derived CPTs
		Module	Average 80th in				
300	2006: 2006 2	Medical/Surgical	\$112 65	\$107 95	\$161 58	\$132 97	\$137 76
	2007: 2007 2		\$117 96	\$107 30	\$173 20	\$133 94	\$138 88
	2008: 2008 1		\$115 17	\$107 65	\$169 69	\$131 79	\$136 65
	2006: 2006 2	Dental	\$102 01	\$97 96	\$135 50	\$114 36	\$114 40
	2007: 2007 2		\$106 69	\$97 95	\$146 53	\$117 37	\$117 51
	2008: 2008 1		\$107 06	\$101 32	\$161 12	\$123 70	\$123 83
350	2006 1: 2006 1	Medical/Surgical	\$111 53	\$105 18	\$163 80	\$130 00	\$135 44
	2006 2: 2006 2		\$111 08	\$106 77	\$175 79	\$132 97	\$137 76
	2007: 2007 2		\$111 28	\$105 31	\$169 58	\$133 94	\$138 88
	2008 1: 2008 1		\$123 11	\$109 00	\$182 39	\$131 79	\$136 65

Notes:

1 The term "Footprint" refers to the set of procedure code/geozip combinations in Dr. Foreman's 300 CPT study and 350 CPT study, respectively

2 In the "Comparison" column, the number before the colon refers to the time period covered by the contributor data used for the comparison. For example, "2006" refers to the whole year of 2006 contributor data. Similarly, "2006 1" refers to the first six months of the 2006 contributor data. The number after the colon refers to the PHCS release used. For example, "2006 2" refers to the second PHCS release of 2006

3 Sources for Medical/Surgical Foreman 300 Footprint data: 2006 - Excel File "Compare 300 CPT 2006_2.xlsx" tab "Ing 2006 v1"; 2007 - Excel File "Comp 300 Ing_07_02 Rev.xlsx" tabs "medsurg06" & "medsurg07"; 2008 - Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "MEDSURG"

4 Sources for Dental Foreman 300 Footprint data: 2006 - Excel File "Ingenix 2006 contributor versus published for top 300 Codes in top 300 GeoAreas.xlsx" tab "2006 Contributor", 2007 - Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "dental07"; 2008 - Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "DENTAL". Values for 2006 were calculated using the Excel File "Ingenix 2006 contributor versus published for top 300 Codes in top 300 GeoAreas.xlsx" produced by Dr. Foreman in the instant matter as noted above. In "Table 21" of his Expert Merits report, Dr. Foreman states that he uses 11,558 CDT/geozip combinations in his comparison of the dental data found in the 2006 contributor data to the second PHCS release of 2005. By removing CDT/geozip combinations from the above-cited Excel File that have "Null" Ingenix values or contributor percentiles less than \$1, we arrive at 11,558 CDT/geozip combinations. This set of combinations has been used to compute the 2006 values. See Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 19

5 Sources for Foreman 350 Footprint data: 2006 - Excel File "Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1", Excel File "Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B"; 2007 - Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1"; 2008 - Excel File "350 2008_1 compare rev.xlsx" tab "Steve 2008_1 compare rev"

6 Sources for PHCS Sources: PHCS 2006 releases 1 & 2, PHCS 2007 release 2, PHCS 2008 release 1

122. Although Dr. Forman's benchmarks reflect particular footprints of the procedure/geozip combinations, they are based on data relevant to PHCS. Not surprisingly, I find that within these limited footprints, the percentile values are highly correlated with the external benchmarks and with the values in the Ingenix Database. These results are presented in Appendix A, but they show that the values in Dr. Foreman's benchmarks follow the same general patterns as the commercial and government benchmarks for the limited set of procedure/geozip combinations that he investigates.
123. Correlations only indicate similar movements in the values, however, and not necessarily *equality* in the values. The contemporaneous claim-weighted results based on Dr. Foreman's dental benchmark values are consistently negative and larger than the claim-weighted averages based on the NDAS benchmark. Dr. Foreman's benchmark is also substantially more negative than comparisons between NDAS and PHCS when all empirical and all CDTs are considered. These results are contrary to the medical and surgical results in section C. It is disturbing that Dr. Foreman's benchmark is so highly

correlated with NDAS and yet the claim-weighted results are so different. I consider other concerns I have regarding Dr. Foreman's dental results in section G.1.

124. In summary, Dr. Foreman purports to address a wide scope of the Ingenix Database using his 300 and 350 Studies but these datasets are actually very limited footprints of the data that Plaintiffs have alleged is biased downward. Dr. Foreman suggests that his analysis of the majority of the contributor claims is sufficient to infer bias for the substantial majority of procedure/geozip combinations that he essentially ignores. His claim-weighted results, however, cannot be extrapolated to the substantial majority of combinations not examined without further consideration of their representativeness. My analysis shows that he is missing important types of combinations such as high-price/low frequency procedures. Thus, it is unlikely that Dr. Foreman's results can be generalized to the whole of the Ingenix database that is the subject of Plaintiffs' allegations of bias.

Table 22: Dental Percent Difference Benchmark Analysis - Claim Weighted

Benchmark	Average Percent Differences			All Empirical & Derived					
	300 CPTs ⁵			All Empirical CPTs ^{1,6}			CPTs ⁶		
	2006	2007	2008 R1	2005	2006	2007	2005	2006	2007
NDAS - 80th Percentile²	-0.3%	-0.8%			-2.1%	-2.5%	-2.1%	-2.6%	
Foreman Dental - 80th Percentile^{3,4}	-4.4%	-8.6%	-5.7%						

Notes:

1. 2006 All Empirical CPT percent difference values taken from Table 16 of the Expert Report of Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010).
2. Comparison of PHCS and NDAS 80th percentile values.
3. Comparison of PHCS and Foreman Benchmark 80th percentile values.
4. Foreman Dental - 80th Percentile value for 2006 was calculated using the Excel File "Ingenix 2006 contributor versus published for top 300 Codes in top 300 GeoAreas.xlsx" produced by Dr. Foreman in the instant matter. In "Table 21" of his Expert Merits report, Dr. Foreman states that he uses 11,558 CDT/geozip combinations in his comparison of the dental data found in the 2006 contributor data to the second PHCS release of 2005. By removing CDT/geozip combinations from the above-cited Excel File that have "Null" Ingenix values or contributor percentiles less than \$1, we arrive at 11,558 CDT/geozip combinations. This set of combinations has been used to compute the Foreman Dental - 80th Percentile 2006 value. See Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 19.
5. Source for data: 300 Study - 2006 - Excel File "Ingenix 2006 contributor versus published for top 300 Codes in top 300 GeoAreas.xlsx" tab "2006 Contributor", 2007 - Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "dental07", 2008 - Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "DENTAL"
6. Source for data: All Empirical and All Empirical & Derived - PHCS 2005 - 2007.

3. Dr. Foreman's Benchmarks and the Commercial Benchmarks Differ on Coverage of High-Price Procedures

125. Unlike the claim-weighted analysis for medical and surgical comparisons reported above, revenue-weighted comparisons with Dr. Foreman's benchmarks differ substantially from my previous findings. In this section, I investigate this result to explore whether Dr. Foreman's benchmarks are systematically missing certain procedure/geozip combinations indicating they suffer from a representativeness flaw.

126. Using the commercial and government benchmarks, I never found a negative revenue-weighted average result. Negative average results, however, are found using Dr. Foreman's benchmarks as shown in Table 23. Comparisons with his benchmarks suggest that PHCS percentile values are less than the benchmark for frequent, high price

procedure/geozip combinations. The results using Dr. Foreman's benchmarks generally are contrary to the results using the commercial and government benchmarks.

127. Expanding from Dr. Foreman's selective footprints to all empirical CPTs or all CPTs, the results in the last six columns of the table become more positive. Since Dr. Foreman claims to have focused on the most common procedures and geozips, these results might indicate that Ingenix generally exceeds the benchmarks for high revenue procedure/geozip combinations.

Table 23: Percent Difference Benchmark Analysis – Revenue Weighted

Benchmark	Average Percent Differences 300 CPTs ⁷			Average Percent Differences 350 CPTs ⁸				All Empirical CPTs ^{1,9}			All Empirical & Derived CPTs ⁹		
	2006	2007	2008 R1	2006 R1	2006 R2	2007	2008	2005	2006	2007	2005	2006	2007
PFR - 75 th Percentile ⁵	6.6%	6.9%			7.3%	8.3%		8.1%	8.0%		9.8%	9.9%	
PMIC - 75 th Percentile ⁵	3.6%				4.7%			3.9%	5.6%		5.7%	7.5%	
MAG - 85 th Percentile ²	4.1%				4.7%			15.5%	7.1%		18.2%	11.6%	
Medicare PSPS - Mean ³	11.6%	10.2%			11.8%	8.1%		14.8%	16.9%		17.6%		
Foreman Medical/Surgical - 80 th Percentile ⁴	-3.1%	-2.8%	0.8%	-3.0%	-1.9%	-2.9%	-2.4%						

Notes:

1. 2005 & 2006 All Empirical CPT percent difference values taken from Table 17 of the Expert Report of Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr 6, 2010) except for MAG - 85th Percentile values

2. Comparison of PHCS 85th percentile value to MAG high value

3. Comparison of PHCS Average value to Medicare Average Charge

4. Comparison of PHCS and Foreman Benchmark 80th percentile values

5. Comparison of PHCS and Benchmark 75th percentile values

6. In the Expert Report of Dr. Robin Cantor for Class Certification (filed Apr 6, 2010), "Revenue Weighed" = "Dollar Weighted"

7. Source for data: 300 Study - Excel File "Compare 300 CPT 2006_2.xlsx" tab "Ing 2006 v1", Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07" & Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "MEDSURG"

8. Source for data: 350 Study - Excel File "Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1", Excel File "Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B", Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1" & Excel File "350 2008_1 compare rev.xlsx" tab "Steve 2008_1 compare rev"

9. Source for data: All Empirical and All Empirical & Derived - PHCS 2005 - 2007

128. To examine the revenue-weighted results further, I remove the influence of claim count and estimate the price-weighted percent difference. These results are shown in Table 24. While revenue-weighted results are percent difference per dollar spent, price-weighted results are percent differences weighted by the price of each combination ignoring the claim frequency. The price-weighted percent differences suggest that Dr. Foreman's footprints miss influential high-price procedures because as the footprint is expanded, the percent differences become substantially more positive. These results are consistent with my revenue-weighted results. The extreme variation between the 300 and 350 results for Dr. Foreman's benchmarks are likely due to the errors in his datasets that I discussed in section B. In particular, using the 300 CPT benchmark, the price-weighted result exceeds 170 percent in 2007 and 2008—an implausible result.

Table 24: Percent Difference Analysis – Price Weighted

Benchmark	Average Percent Differences				Average Percent Differences				All Empirical & Derived				
	300 CPTs ⁶		350 CPTs ⁷		All Empirical CPTs ⁸		CPTs ⁸						
	2006	2007	2008 R1	2006 R1	2006 R2	2007	2008	2005	2006	2007	2005	2006	2007
PFR - 75 th Percentile ⁴	6.2%	8.8%			6.0%	12.5%		13.2%	14.3%		84.1%	88.4%	
PMIC - 75 th Percentile ⁴	2.3%				4.1%			7.7%	11.3%		83.0%	85.1%	
MAG - 85 th Percentile ¹	2.8%				4.4%			24.5%	19.1%		24.5%	19.1%	
Medicare PSPS - Mean ²	29.0%	16.4%			23.0%	12.0%		24.3%	20.9%		243.7%		
Foreman Medical/Surgical - 80 th													
Percentile ³	-5.8%	170.0%	236.5%	3.5%	1.4%	-3.9%	7.8%						
<u>Notes:</u>													
1 Comparison of PHCS 85th percentile value to MAG high value													
2 Comparison of PHCS Average value to Medicare Average Charge													
3 Comparison of PHCS and Foreman Benchmark 80th percentile values													
4 Comparison of PHCS and Benchmark 75th percentile values													
5 In the Expert Report of Dr. Robin Cantor for Class Certification (filed Apr 6, 2010), "Revenue Weighed" = "Dollar Weighted"													
6 Source for data: 300 Study - Excel File "Compare 300 CPT 2006_2.xlsx" tab "Ing 2006 v1", Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "medsurg07" & Excel File "Comp 300 Ing_08_08 Rev.xlsx" tab "MEDSURG"													
7 Source for data: 350 Study - Excel File "Compare_Contrib_2006_1.xlsx" tab "Compare_Contrib_2006_1", Excel File "Compare_Contrib_2006_1B.xlsx" tab "Compare_Contrib_2006_1B", Excel File "Compare_Contrib_2007_1.xlsx" tab "Compare_Contrib_2007_1" & Excel File "350 2008_1 compare rev.xlsx" tab "Steve 2008_1 compare rev"													
8 Source for data: All Empirical and All Empirical & Derived - PHCS 2005 - 2007													

129. In summary, these results indicate that Dr. Foreman's footprints are systematically excluding high price/low frequency procedures. Plaintiffs' experts have opined that there is evidence that the alleged bias is more severe for high-price procedures. The omission of high price/low frequency data, however, undermines Dr. Foreman's analysis and the conclusions based on it.

F. Dr. Foreman's Analysis of the Alleged Flaws, Which Are Necessary for His Damage Methodology, Are Unreliable

130. As explained above, Dr. Foreman's benchmarks do not correct the methodological flaws alleged by Plaintiffs. In particular, although Plaintiffs have repeatedly referenced concerns about representativeness, screening out legitimate data, and use of derived data, Dr. Foreman's benchmarks fail to correct these flaws properly, completely, or both. My analysis shows that his methodology to investigate some of the flaws frequently referenced by Plaintiffs is seriously deficient and leads to incorrect inferences about the existence and direction of any systematic bias. Based on my analyses demonstrating that Dr. Foreman's inferences about the biases from these alleged flaws are incorrect, I conclude that he has not established the proper foundation for his subsequent damage calculations.

1. Dr. Foreman's Analysis of Representativeness Is Biased and Improper

131. Dr. Foreman examines the mean billed charges for “All Contributor Medical Surgical Procedures in 2007 by Contributor”¹²⁷ to test whether the data contributed by payers to Ingenix for use in PHCS are representative of the population of billed charges. As I have noted, Dr. Foreman also conducts a selected analysis of New York State but it is implausible that this analysis could be representative of all states covered by the Ingenix Database. I therefore focus my review on Dr. Foreman’s national analysis. In that analysis, Dr. Foreman reports that he eliminated Aetna and CIGNA data from the contributed data supposedly “to show the potential impact of the unknown missing contributors’ data.”¹²⁸ Dr. Foreman claims that this results in an increase of 12% in the mean billed charge for all of the “medical surgical contributor data.”¹²⁹
132. Dr. Foreman’s analysis apparently is a crudely executed application of a post-stratification methodology.¹³⁰ Properly applied, a post-stratification methodology can be used to correct for sampling bias, but Dr. Foreman has not applied this methodology properly. In his application, Dr. Foreman has eliminated Aetna and CIGNA from the calculation, and correspondingly has increased the significance of other payers in the contributor data. Without explanation, Dr. Foreman retains the data he reports for UnitedHealth and WellPoint, other payers who have been linked to ONET litigation.¹³¹ To show the implications of this strategy, I use, but do not adopt or endorse, Dr. Foreman’s data. Table 25 shows the results of removing Aetna and CIGNA, and produces Dr. Foreman’s positive 12 percent difference in the resulting mean billed charge.¹³² It also shows that removing UnitedHealth alone causes a *negative* 17 percent change in the mean billed charge. When Aetna, CIGNA, UnitedHealth and WellPoint are removed the mean billed charge declines by 8 percent. In other words, by removing all of the large managed care companies that are the subject of the ongoing UCR-related litigation (Aetna, CIGNA, United, WellPoint), the change in the data runs in the opposite direction from Dr. Foreman’s hypothesized representativeness bias. It is only by selectively removing just Aetna and CIGNA data that Dr. Foreman can show a supposed downward bias, but there is no scientifically sound basis (and none offered by Dr. Foreman) for such an approach. Dr. Foreman’s arbitrary decision to eliminate only Aetna and CIGNA data thus directly leads to his finding that there is a downward bias.

¹²⁷ See Foreman Report at ¶ 156.

¹²⁸ See Foreman Report at ¶ 158.

¹²⁹ *Ibid.*

¹³⁰ Post-stratification methods group or weigh data to conform to expected compositions or patterns. See, e.g., Henry, G.T. 1990. *Practical Sampling*. Newbury Park, CA: SAGE Publications at p. 130.

¹³¹ Contributor ID 417, reported by Dr. Foreman as Empire BC/BS in “Table 1” and as WellPoint in “Table 2,” is Empire BC/BS, currently a subsidiary of WellPoint.

¹³² For this analysis, I am using the equation that Dr. Foreman uses to measure percent differences.

Table 25: Foreman “Table 2” – Representativeness: Variation in Mean Billed Charge by Inclusion/Exclusion of Contributors Relative to Total Medical-Surgical

		<u>Percent Difference</u>
	<u>Foreman</u>	<u>between Mean & Mean</u>
	<u>Mean</u>	<u>of Total Medical</u>
	<u>Charge</u>	<u>Surgical</u> ²
[A]	[Total Medical Surgical]	\$185.97
[B]	Aetna	\$140.20
[C]	CIGNA	\$117.85
[D]	United	\$252.92
[E]	Wellpoint	\$150.07
 [A-B-C]	Total-Aetna-CIGNA	\$208.28
[A-D]	Total-United	\$154.17
[A-B-C-D]	Total-Aetna-CIGNA-United	\$170.18
[A-B-C-D-E]	All Other	\$171.86

Notes:

1. Source: Expert Report of Stephen Foreman (CORRECTED), Ph.D., J.D., M.P.A., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 2.

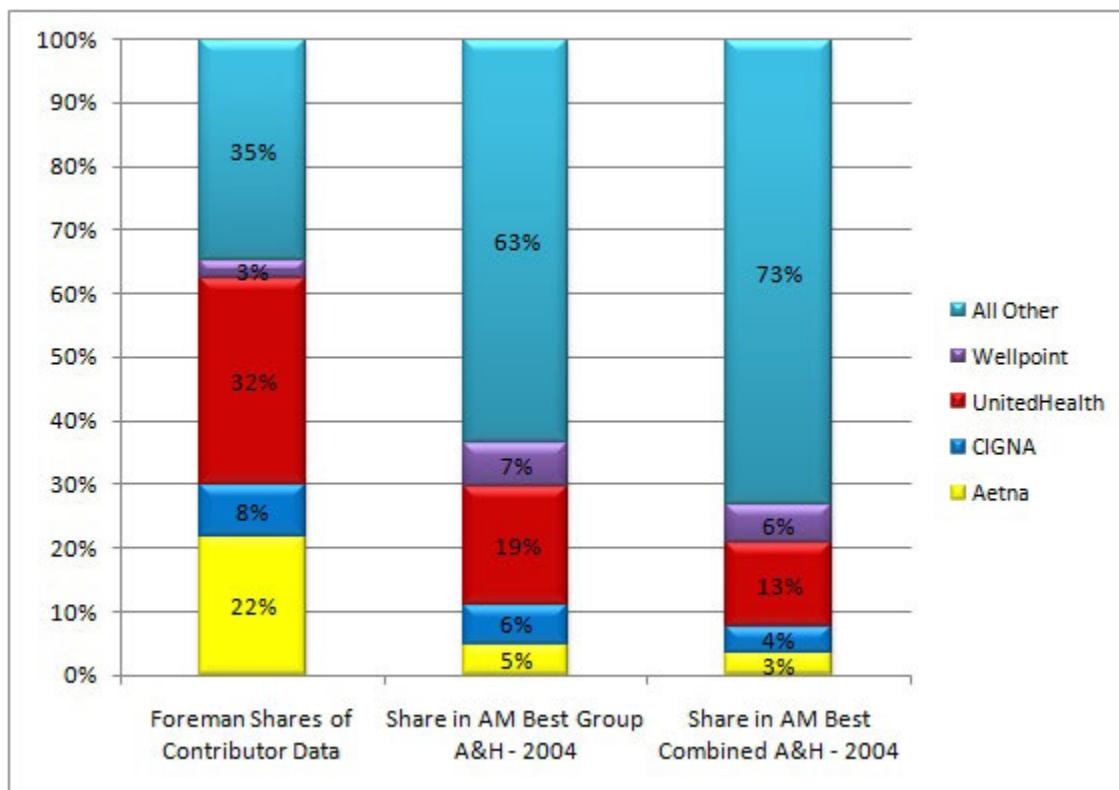
2. As in “Table 2” of Dr. Foreman’s Affirmative Merits Report, “UnitedHealth” is contributor ID number 1, “WellPoint” is contributor ID number 417, “Aetna” includes contributor ID numbers 375 and 239, and “CIGNA” includes contributor ID numbers 411 and 394.

3. “Percent Difference between Mean & Mean of Total Medical Surgical” equals the mean in each row minus the mean of total medical surgical (\$185.97) divided by the mean of total medical surgical.

133. Given Aetna’s and CIGNA’s positions in the health insurance markets, however, it seems reasonable to expect that their data would be included as some proportion of a sample free of the alleged representativeness flaw. A zero weight makes no empirical or statistical sense for Dr. Foreman’s sample weighting. A properly executed method to assess representativeness might indeed compare contributor shares to actual market shares. If the contributor shares differ substantially from reported market shares, this information can be used make them consistent with market share in the actual payer market. Regarding market shares, Dr. Rausser cites and uses 2004 data from AM Best.¹³³ Figure 2 shows the AM Best information has shares that differ from proportions in the contributor data.

¹³³ See Rausser Report at notes 30 and 153.

Figure 2: Contributor Share¹³⁴



134. I use the market share data to recalibrate the contributor shares in the data sponsored by Dr. Foreman. Application of the 2004 market share weights for Group Accident and Health (“A&H”) results in a decline in the overall mean charge in the contributor data from approximately \$186 to \$180—a 3 percent decline—as shown in Table 26.¹³⁵ I also conduct sensitivity analysis using Combined Group and Individual A&H market shares and a more recent year of data. The sensitivity results vary from a positive 1 percent to a negative 5 percent. In this analysis, a negative result indicates that the values in the Ingenix data are higher than the values in the re-weighted sample, which is a result that runs counter to Dr. Foreman’s hypothesis that the supposed lack of representativeness in the Ingenix data leads to a downward bias in the Ingenix percentile values.

¹³⁴ See Foreman Report at “Table 2”; AM Best Company. 2005. *Best’s Aggregates & Averages, Life/Health, United States & Canada*. Oldwick, NJ: Best’s Publishing System at pp. 236-241, 244-249

¹³⁵ We attempted, but were unable, to replicate Dr. Foreman’s selection of CPT codes used for this analysis based on the materials he produced for his report. However, we conducted the analysis not only as shown here with Dr. Foreman’s own contributor data, but also with several selections of contributor data taken from the original set. These selections include (1) CPT codes 10021-69990, 90281-99199 & 99500-99607, (2) 00100-01999, 70000-99999 & 10000-69999, (3) 10000-99999 & (4) all CPT codes with the variable “PROC_TYPE” equal to “C”.

Table 26: Foreman “Table 2” – Representativeness: Weighted Average Mean Billed Charge Adjusted by Market Share

		<u>Foreman Mean Charge - 2007</u>	<u>Foreman Mean Charge - 2004</u>	<u>Foreman Mean Charge - 2008</u>	<u>Percent Difference between</u>	
					<u>Mean & Mean of Total Medical Surgical - 2004</u>	<u>Percent Difference between Mean & Mean of Total Medical Surgical - 2008 Base</u>
					<u>Base</u>	<u>Base</u>
[A]	[Total Medical Surgical]	\$185 97				
	AM Best Group A&H ^{3,4}		\$180 48	\$186 98	-3%	1%
	AM Best Combined A&H ^{3,4}		\$177 57	\$183 29	-5%	-1%

Notes:

1 Source: Expert Report of Stephen Foreman (CORRECTED), Ph D , J D , M P A , In Re: Aetna UCR Litigation (MDL No 2020 filed Aug 9, 2010) at Table 2

2 As in "Table 2" of Dr Foreman's Affirmative Merits Report, "UnitedHealth" is contributor ID number 1, "WellPoint" is contributor ID number 417, "Aetna" includes contributor ID numbers 375 and 239, and "CIGNA" includes contributor ID numbers 411 and 394

3 "Percent Change" equals the mean in each row minus the total mean (\$185 97) divided by the total mean

4 Source - "AM Best" Data: AM Best Company 2005 Best's Aggregates & Averages, Life/Health, United States & Canada Oldwick, NJ: Best's Publishing System, 2004 at pp 236-241 and pp 244-249; AM Best Company, 2009 Best's Aggregates & Averages, Life/Health, United States & Canada Oldwick, NJ: Best's Publishing System, 2009 at pp 235-241 and pp 244-248

5 AM Best Group A&H Mean value is a weighted average calculated by multiplying the AM Best Group A&H share percentage for each company and row [A-B-C-D-E] by their respective mean values and summing the results. The same calculation is done for the AM Best Combined A&H Mean value, except using the AM Best Combined A&H share percentages

6 Because the companies listed on the AM Best lists do not match the companies listed in the Contributor data set exactly, the row [A-B-C-D-E] does not include the same companies for all calculations

135. Based on this analysis, I find that Dr. Foreman's results for the bias due to representativeness are not supported by a proper method to reweight the data. The results based on the reported market share data fail to support his inference that the Ingenix sample of data biases the percentile results downward and therefore fails to support damages due to the alleged representativeness flaw.

2. Plaintiffs' Experts' Analysis of the High-Low Screen Is Unreliable

136. Dr. Foreman investigates the alleged bias of the so-called "high-low screen" used by Ingenix to remove outliers from the contributor data. Dr. Foreman's analysis relies on Aetna and CIGNA data rather than the contributor data to investigate the bias. Based on his analysis, Dr. Foreman purports to find empirical support that "when applied to a right skewed distribution [the high-low screen] biases higher percentile values downward."¹³⁶

137. In contrast, Dr. Slottje examines the effect of the high-low screen on the contributor data directly by adding back the records that the screen removed. Based on his analysis, Dr. Slottje finds that there is a positive or no effect on the 80th percentile values for approximately 92 percent of the CPT/geozip combinations.¹³⁷ These results fail to support an inference that the screen leads to a systematic downward bias.

138. In this section, I present the results of a simulation designed to investigate whether Dr. Foreman's or Dr. Slottje's results are reasonable. My simulation examines the effects of the various screens described above on right-skewed distributions. My simulation varied assumptions about the underlying levels of billed charges and the variation in billed charge values to address the robustness of the results. I find that when the high-low

¹³⁶ See Foreman Report at ¶ 210.

¹³⁷ See Expert Report of Dr. Daniel J. Slottje on Class Certification Issues, Franco v. Connecticut General Life Insurance Co. (Jun. 30, 2010) at pp. 9-10. The materials in Dr. Slottje's June 30th report in the matter of Franco v. Connecticut General Life Insurance Co. are incorporated in the instant matter. See Affirmative Merits Expert Report of Dr. Daniel J. Slottje, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at p. 2.

screen is defined properly, it can sometimes decrease, increase, or leave unchanged the value of the 80th percentile for a subject distribution of billed charges. This simulation is thus consistent with Dr. Slottje's empirical results and contradicts the hypothesis of Plaintiffs' experts that the high-low screen leads to a systematic downward bias in the Ingenix percentile values. Moreover, I find that the same results are obtained when the high-low screen is applied over many time periods.

139. In his analysis of the high-low screen, Dr. Foreman does not actually use the high-low screen used by Ingenix.¹³⁸ Instead, he uses a variation of the scrubbing rule based on the Tukey method for identifying outliers.¹³⁹

The traditional Tukey screen is:

Screen If Charge Is > (75th + (1.5 * IQR))
Screen If Charge Is < (25th - (1.5 * IQR))¹⁴⁰
Where IQR is the interquartile range, 75th is the 75th percentile value, and 25th is the 25th percentile value for the distribution.

The Tukey screen that Dr. Foreman uses ("the Foreman screen") is:

Screen If Charge Is > (80th + (1.5 * IQR))
Screen If Charge Is < (50th - (1.5 * IQR))¹⁴¹
Where 80th is the 80th percentile value, and 50th is the 50th percentile value for the distribution.

The high-low screen used by Ingenix that apparently is understood by Plaintiffs' experts is:

Screen if charge is > RV x per 80 x hifct
Screen if charge is < RV x per 50 x lowfct¹⁴²
Where RV is the relative value for the procedure and per 80 and per 50 are defined conversion factors.

140. As Dr. Siskin asserts:

Translated, the high formula (*i.e.*, (i) above) means that Ingenix eliminates a contributed charge if it exceeds the product of the relative value for that CPT code multiplied by the 80th percentile for the combined data in the CPT code range (*the "per 80"*) multiplied by an arbitrary high factor

¹³⁸ Dr. Foreman acknowledges in his deposition that he did not analyze the actual Ingenix high-low screen in his report (*See* Foreman Merits Deposition Volume II at pp. 105:15-21, 106:13-16).

¹³⁹ *See* Foreman Report at ¶ 178.

¹⁴⁰ *See* Tukey, J.W. 1977. *Exploratory Data Analysis*. Philippines: Addison-Wesley Publishing Company, Inc at p. 44.

¹⁴¹ Dr. Foreman explains: "We developed values for the 25th, 50th, 75th, and 80th percentiles of billed charges, the inter quartile range (IQR=75th-25th), the screen factor (1.5*IQR), the high screen value (80th+(1.5*IQR)) and the low screen value (50th-(1.5*IQR))." *See* Foreman Report at ¶ 178.

¹⁴² *See* Plaintiffs' Expert Report dated April 6, 2010 of Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the "Siskin Class Certification Report") at p. 21.

number (hifct) determined by Ingenix.¹⁴³

The values of the high and low factors (“hifct” or “fee high” and “lowfct” or “fee low”) that are used in the Common Scrubber formula are arbitrary.

Very similar high and low factor values have been in use since 1992.

Ingenix uses 1.95 as the high factor for all medical procedures; 1.8 as the high factor for all radiology procedures; 1.88 as the high factor for all laboratory procedures; and 1.9 as the high factor for all surgical procedures.¹⁴⁴

141. Based on Dr. Siskin’s explanation and available testimony, I do not believe that Dr. Foreman’s screen is a reasonable or even close approximation to the screen used by Ingenix. His formula ignores the relative value, the “per 80” and “per 50” factors, and the high and low factors of the Ingenix screen as described by Dr. Siskin. The high-low screen does not depend directly on the 80th percentile value or the IQR of the distribution for a subject CPT/geozip combination. I show in Appendix D that these various screens can be related to each other by defining a factor “Beta” for the high-low screen that captures the ratio between the conversion factors multiplied by the procedure’s relative value and the percentile values of the subject distribution. The Beta value allows direct comparisons across the various screens because now they are all functions of the 50th and 80th percentile values of distributions of billed charges by CPT/geozip.
142. My simulation produces data sets of 100,000 records each, lognormally distributed with various levels of means and standard deviations.¹⁴⁵ I selected the lognormal distribution because it is a standard right-skewed distribution. Preliminary analysis indicated that the percentage differences between the screened and the unscreened data are similar across different mean levels but affected by the standard deviation. I therefore provide here results averaged across different mean levels and categorized by the standard deviation as indexed by the coefficient of variation (“CV”), a standard measure of variation in statistics.
143. Figures 3 and 4 show results for two different assumptions about Beta and seven assumptions about the CV. The vertical axis measures the percent difference between the 80th percentile values of the unscreened and screened data. Values greater than zero indicate an increase in the screened 80th percentile value compared to the unscreened data. Values less than zero indicate a decrease in the screened 80th percentile value compared to the unscreened data. The green results pertain to the high-low screen used by Ingenix, the red results pertain to the Foreman screen, and the grey hatched results pertain to the traditional Tukey screen. The figures show that for Beta = 0.5 and Beta = 1, all screens decrease the 80th percentile values and this effect becomes more negative with increasing variance in the distribution.

¹⁴³ See Siskin Class Certification Report at p. 22 (emphasis added).

¹⁴⁴ See Siskin Class Certification Report at note 10.

¹⁴⁵ Note that the 100,000 records are generated randomly from the distribution. Each time the simulation program is executed, the resulting dataset will be different, but there is no substantive change in the results presented herein.

Figure 3: Outlier Screen Simulation, Beta=0.5

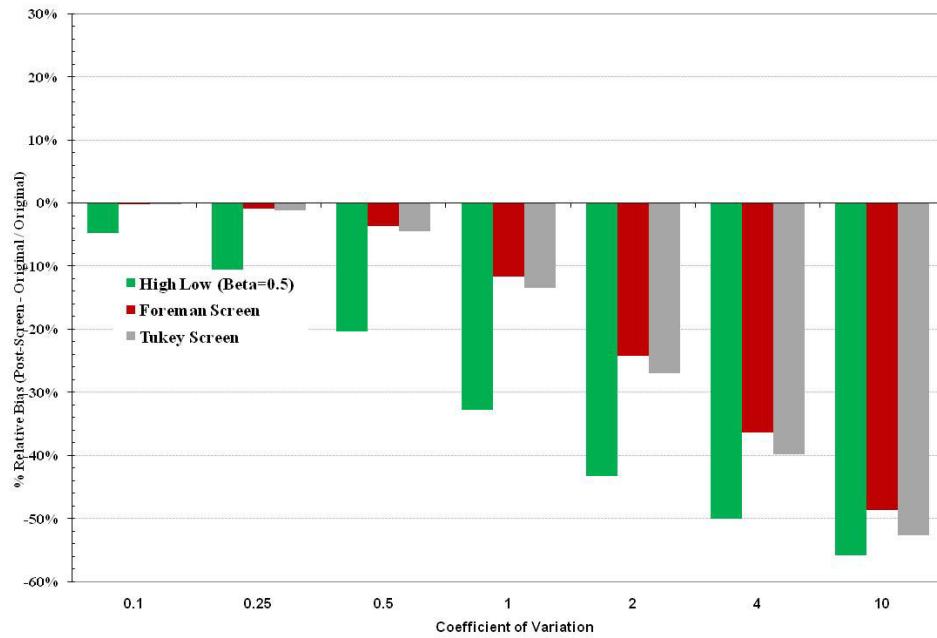
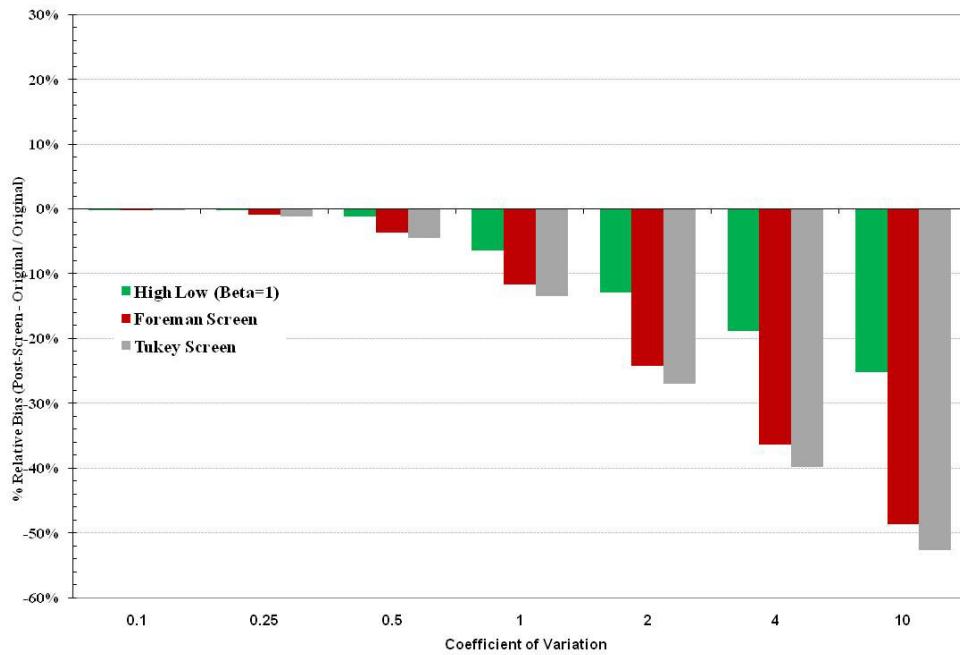


Figure 4: Outlier Screen Simulation, Beta=1.0

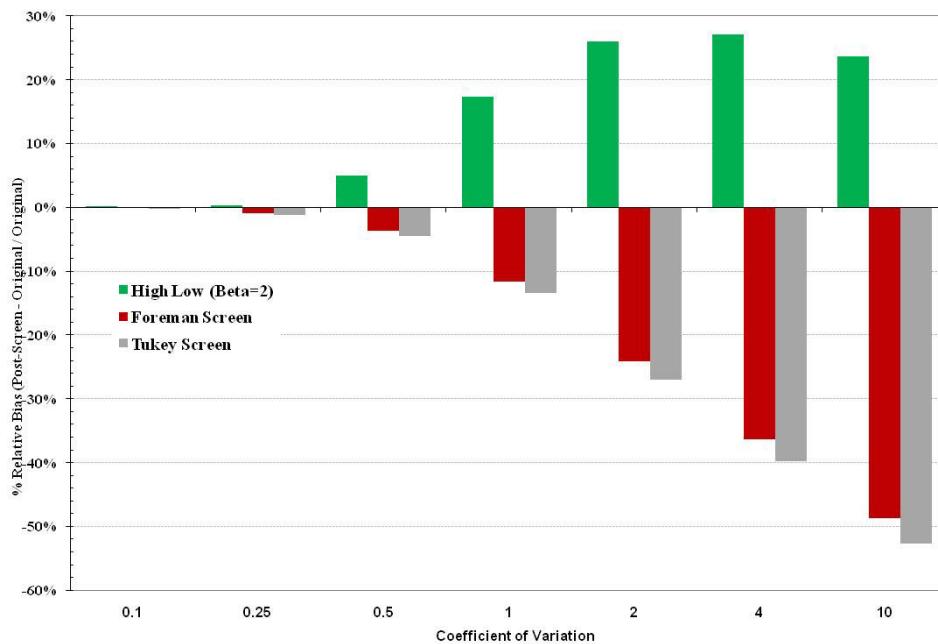


144. For Beta = 0.5, both the Foreman screen and the Tukey screen result in less decline in the value of the 80th percentile than the high-low screen. For, Beta = 1, the high-low screen

results in less decline than the Foreman and Tukey screens. The reason for this switch in positions is the amount of high and low claims that are removed by the screen. With low Betas, the high-low screen removes more high-value than low-value claims. At Beta = 1, this is less so, and importantly, the Foreman and Tukey screens are removing almost no low values because they are a simple multiple of the interquartile range. With higher variation, less low value data will be screened out using the Tukey or the Foreman screens. Since the high-low screen does not depend on IQR, it continues to screen out low values.

145. Figure 5 shows the results when Beta = 2. The high-low screen, because it continues to remove low-value claims and will remove a greater number of them for higher values of Beta, now results in an *increase* in the 80th percentile values for most of the assumptions about variation. The Foreman and the Tukey screens continue to result in a reduction because they are not affected by the relationship to the “per 80” or “per 50”, i.e., they are not affected by Beta. These screens depend only on the values and the width of the IQR—reflecting variation in the values. These results support the results that Dr. Slottje found in his analysis—sometimes the high-low screen can increase, leave unchanged, and decrease the higher percentile values. Repeated simulations indicate that the “switching” point from a negative to a positive bias for the high-low screen under these conditions occurs at approximately Beta = 1.4.

Figure 5: Outlier Screen Simulation, Beta=2.0



146. Using the simulations, I also investigated whether a switch in the bias could be produced with the Foreman screen. For different levels of CV (variation), I compared the non-screen percentile values to the values using only the Foreman screen. Table 27 shows that for various assumptions about the mean levels and variation, the Foreman screen always reduces the unscreened 80th percentile value. In the table, the “no screen” values are always larger than the Foreman screen values. Based on these simulations, I conclude that Dr. Foreman used a screening procedure in his analysis to represent the results of the Ingenix high-low screen that likely would always reduce the 80th percentile values. His screen is a biased representation since it cannot produce the increases in the 80th percentile values as found with the high-low screen when it is properly defined.

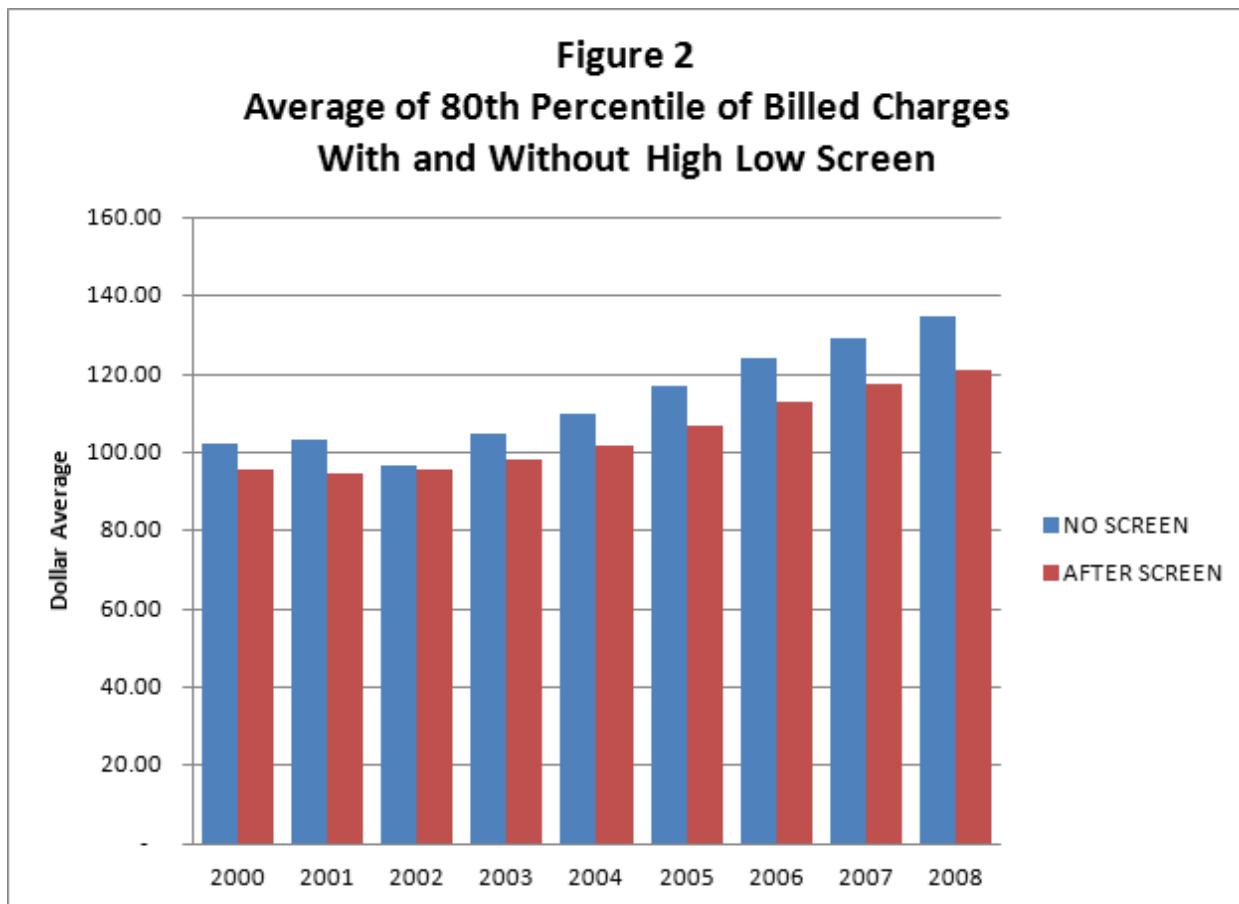
Table 27: Simulated Percentile Values, No Screen v. Foreman Screen

Mean	CV (Standard Deviation/Mean)									
	0.1		0.5		1		2		4	
	No Screen	Foreman Screen	No Screen	Foreman Screen	No Screen	Foreman Screen	No Screen	Foreman Screen	No Screen	Foreman Screen
\$50	\$54.10	\$54.10	\$66.60	\$64.20	\$71.20	\$63.20	\$65	\$49.40	\$50	\$32
\$100	\$108.20	\$108.10	\$133.10	\$128.30	\$142.50	\$125.40	\$13,012	\$99.70	\$100	\$63.50
\$500	\$541.10	\$540.70	\$665.50	\$643.20	\$712.50	\$632.10	\$650.40	\$494.50	\$500	\$317.20
\$1,000	\$1,082.20	\$1,081.60	\$1,331.10	\$1,283.10	\$1,424.90	\$1,256.60	\$1,300.80	\$985.30	\$1,000	\$636.60
\$5,000	\$5,410.90	\$5,408.10	\$6,655.40	\$6,412.10	\$7,124.60	\$6,314.10	\$6,504.10	\$4,940.50	\$5,000.10	\$3,180.90
\$10,000	\$10,821.80	\$10,810.20	\$13,310.80	\$12,796.90	\$14,249.30	\$12,550.90	\$13,008.20	\$9,897.60	\$10,000.20	\$6,425

147. In his report, Dr. Foreman also analyzes the effect of his screen on CIGNA data over time. Dr. Foreman claims that “the high-low screen is developed each year to eliminate data for the succeeding year.”¹⁴⁶ Based on this view, he applied the screen serially over time. He finds that the application of his screen to the data generates an increasing difference between the average 80th percentile dollar amounts of billed charges. Dr. Foreman’s results are reprinted in Figure 6.

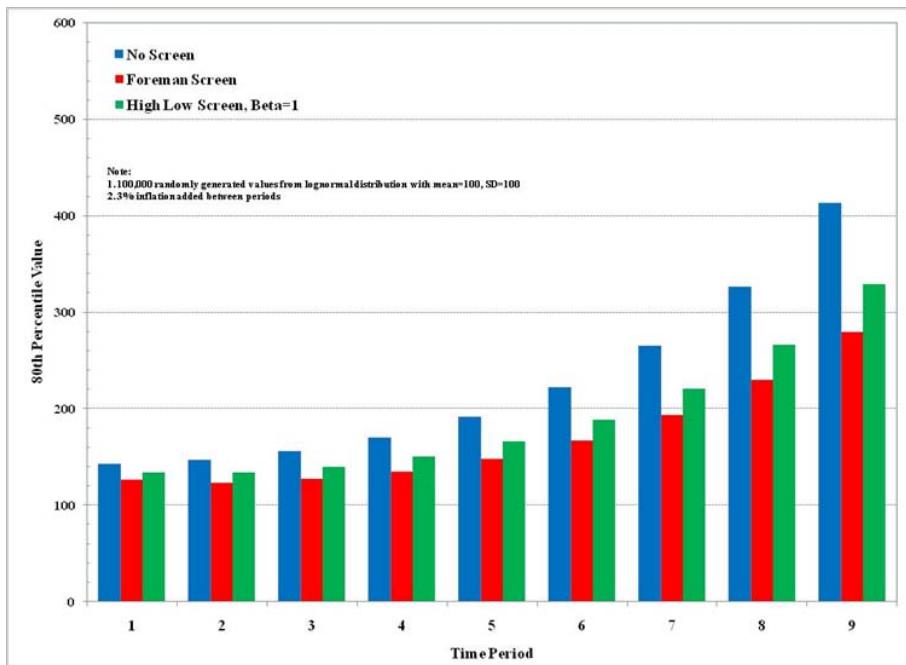
¹⁴⁶ See Foreman Report at ¶ 176.

Figure 6: Foreman Report Figure 2



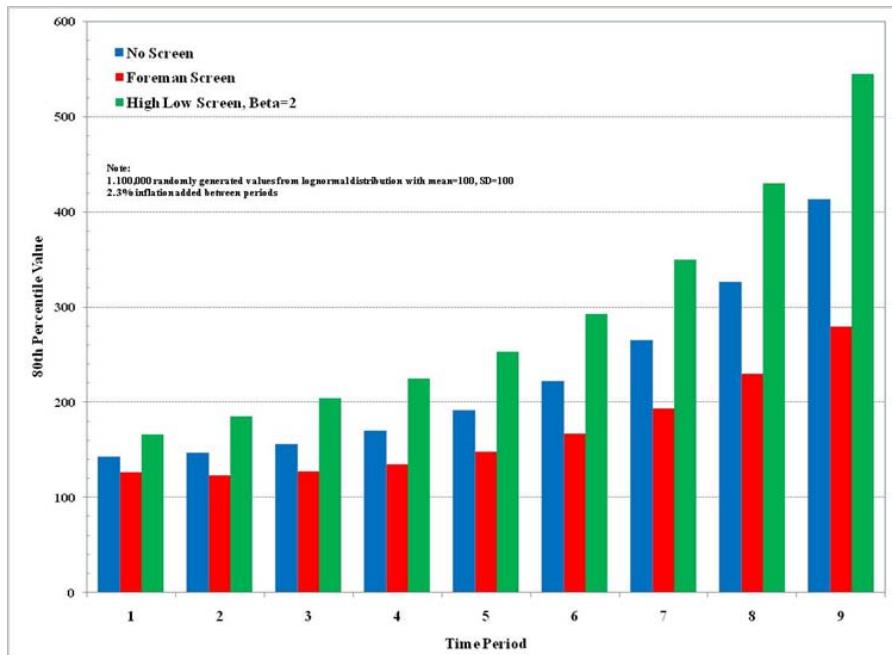
148. I used my simulation model to investigate whether Dr. Foreman's serial results hold for the high-low screen properly defined. To address the time series aspects of the comparison, I modified the model to use lagged values of the 50th and 80th percentile values to determine the screens—one of the alleged flaws in the Ingenix scrubbing protocol. To make the simulation mimic Dr. Foreman's use of actual data, I added a 3 percent annual escalation factor to the values of the annual data to simulate inflation in the billed charges over time.
149. Figure 7 shows the results for Beta = 1 and CV = 1. Beginning with an average level of approximately \$150, the simulation shows that under these conditions both the Foreman and the high-low screens increasingly diverge from the "no screen" case over the nine periods. These results behave much in the same way as Dr. Foreman's original results above.

Figure 7: Outlier Screen Over Time, 3% Inflation, Beta=1 (CV=1.0)



150. Figure 8 shows the results when Beta = 2 is assumed. Despite using lagged data for determining the screens and the inclusion of a 3 percent inflation factor, the value of the 80th percentile is *larger* for the high-low screen than for the “no screen” case. The Foreman screen, however, continues to reduce the 80th percentile value.

Figure 8: Outlier Screen Over Time, 3% Inflation, Beta=2.0, (CV=1.0)



151. My simulation results support the conclusion that the high-low screen used by Ingenix does not necessarily lead to a systematic bias downward in the upper percentiles values. Depending on the relationship between the actual distribution and the combined data used to estimate the “per 80” and the “per 50” conversion factors, it might lead to values that generally exceed the unscreened data. In contrast, the Tukey and Foreman screens fail to produce any results that increase the 80th percentile value. These results support Dr. Slottje’s empirical findings and demonstrate why Dr. Foreman’s approximation for the high-low screen easily led him to incorrect findings about the alleged bias.

3. Dr. Foreman’s Analysis of the Minimum Sample Size Is Incorrect

a) Dr. Foreman Fails to Understand the Sampling Problem for His Minimum Sample Size Analysis

152. Based on his percentile comparisons, Dr. Foreman implies that the proper minimum sample size for the reliable estimation of percentile values is two orders of magnitude greater than the current count used by Ingenix.¹⁴⁷ Based on his report and his production materials, I find that Dr. Foreman incorrectly reached this conclusion. In his report, Dr. Foreman references a particular website as an example of the foundation he used to select a sample size of 255 as the minimum number of claims necessary to estimate the 80th percentile value for a CPT/geozip.¹⁴⁸ However, the power test that this website reflects is for estimating the sample proportion in a survey. This is a test based on a binomial

¹⁴⁷ See Foreman Report ¶ 16, ¶ 245.

¹⁴⁸ See Creative Research Systems, “Sample Size Calculator,” available at <http://www.surveysystem.com/sscalc.htm> (“Sample Size Calculator”) (last visited Oct. 6, 2010).

distribution, rather than a normal distribution and is contrary both to the subject problems and to the assumptions that Dr. Foreman states in his report.¹⁴⁹

153. Dr. Foreman provides the following information about his sample size calculations:

If we require confidence intervals of 2.4 so the 80th does not overlap with the 75th or the 85th, and if we would like to say with 95% confidence that the 80th percentile reported is the true 80th for the population of billed charges, and if there are 300 billed charges for the CPT / geozip combination during the year, *we will need 254 observations for accuracy*, far greater than the nine reported by Ingenix.¹⁵⁰

154. The sample website Dr. Foreman references for this calculation is sponsored by Creative Research Systems. The site states that “This Sample Size Calculator is presented as a public service of Creative Research Systems survey software. You can use it to determine how many people you need to interview in order to get results that reflect the target population as precisely as needed.”¹⁵¹ The site reports formulas used in its sample size calculator that are for a binomial distribution used for a proportion.¹⁵² I entered Dr. Foreman’s precision targets into the site’s calculator to investigate whether Dr. Foreman used it for the conclusion in his report that 254 observations are needed for accuracy. The results are reproduced in Figure 9 and seem to confirm that he did indeed use this formula for his analysis of minimum sample size.

¹⁴⁹ Dr. Foreman’s footnote 82 reads as follows: “Assuming a normal distribution which physician billed charges are not. A distribution skewed right will require even more observations in the sample.” See Foreman Report at p. 64.

¹⁵⁰ See Foreman Report at ¶ 245 (emphasis added) and note 81.

¹⁵¹ See Sample Size Calculator (last visited Oct. 6, 2010).

¹⁵² See Creative Research Systems, “Sample Size Formulas for our Sample Size Calculator,” available at <http://www.surveysystem.com/sample-size-formula.htm> (last visited Oct. 6, 2010).

Figure 9: Foreman Sponsored Sample Size Calculation Website¹⁵³

The figure consists of two side-by-side screenshots of web-based calculators.

Determine Sample Size

Confidence Level: 95% 99%

Confidence Interval: 2.4

Population: 300

Calculate **Clear**

Sample size needed: 254

Find Confidence Interval

Confidence Level: 95% 99%

Sample Size: [empty input]

Population: [empty input]

Percentage: 50

Calculate **Clear**

Confidence Interval: [empty input]

155. If true, this information indicates that Dr. Foreman fundamentally misunderstood the sampling problem faced by Ingenix.¹⁵⁴ PHCS is providing interval percentile values for

¹⁵³ See Sample Size Calculator (last visited Oct. 6, 2010).

¹⁵⁴ In his deposition, Dr. Foreman admits to using this calculator as well as the mirror calculator that solves for confidence interval that is based on the same incorrect assumptions about the sampling problem.

A.[I went] on the internet to power analysis calculators and plugged values. So, you know, starting with the confidence interval of 2.5, actually put in numbers of samples and 80th percentile for example, increased the sample size until the confidence interval gets less than 2.5.

See Foreman Merits Deposition Volume I at pp. 171:11-24.

Q. Dr. Foreman the court reporter has handed you what is marked as Exhibit 39. It is our printout of a web site [...] I would like to point you to page 62 of your report, footnote 82.

[...]

Q. Is this the calculator that you completed to calculate the sample size of 255 that you used in your report?

A. [...] I did I believe in as I cited in the report go to this, and plugged some numbers in this calculator in order to do my own analysis of that.

[...]

A. I think that I ended up with putting a population in there of 300 sample size of 250 and a percentage of 80.

Q. How did you decide of a population size of 300?

billed charges, not an estimate of a proportion. Dr. Foreman's referenced formula for sample size is incorrect for the subject problem. Because the percentile values depend on non-parametric distributions, there is no simple method to estimate the minimum sample size to achieve the precision goals proffered by Dr. Foreman.

156. Dr. Foreman has provided no foundation for his target precision goals. In this matter, Dr. Foreman has reached various opinions regarding the issues of target precision and minimum sample size. In his prior report, Dr. Foreman states:

A five percent margin for error and a ten percent percentile range (a difference of no more than five percentiles in both directions from the 80th percentile, for example) would require approximately 80 billed charge claims records – many more than ten.¹⁵⁵

157. Notably, FAIR Health has sponsored a minimum sample size far below Dr. Foreman's value. There is information indicating that Fair Health has determined only 40 claims are sufficient to meet its precision goals.¹⁵⁶ In a recent description of its methodology for estimating percentile values, FAIR Health states:

In the event that there are fewer than 40 observations for a given CPT-geozip cell, FAIR Health will employ the following methodology:

- If there are fewer than 40 observations in a cell, FAIR Health will use claims data from the prior five years on a graduated basis proceeding year to year as necessary to broaden the cell to the requisite 40 observation threshold (adjusting charges from prior years using the Consumer Price Index);
- If the above adjustment yields fewer than 40 observations, FAIR Health will use two-digit geozips to broaden the cell;
- If the above adjustment still yields fewer than 40 observations, FAIR Health will use a state average to fill the cell;
- If the above adjustment yields fewer than 40 observations, FAIR Health will use the regional average to fill the cell; and
- If the above adjustment yields fewer than 40 observations, FAIR Health will use the national average to fill the cell.¹⁵⁷

158. Further information about the analysis used to determine 40 as the minimum sample size is not available in the FAIR Health report, however, I note that data pooling over time, combining geozips, and national averages are all considered in the proposed methods. FAIR Health is using many of the same standard methods that industry uses in the management of large datasets. Moreover, the methods above are *automatic*. There is no

A. Basically, I was trying to generate a confidence interval of 2.5 plus or minus.

See Foreman Merits Deposition Volume II at pp.208:9-210:11.

¹⁵⁵ *See* Expert Report of Stephen Foreman, PhD, JD, MPA, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) at ¶ 131.

¹⁵⁶ There is also information from Ingenix that Dr. Foreman reviewed which indicates only modest gains in precision can be achieved with claim counts larger than 50. *See* INGENIXMDL000666852 – Determination of N

¹⁵⁷ *See* FAIR Health Summary at pp. 2-3.

discussion of using a manual review of datasets “approximately” at 40 observations to decide the next steps to be taken to construct the distribution of billed charges.

b) Dr. Foreman’s Analysis of the Small Numbers “Problem” Is Confounded By His Failure to Track Derived Data Properly

159. Dr. Foreman’s approach to testing the alleged bias from using small claim counts provides another example of his selective use of data. To investigate the alleged bias of small claim counts from which percentile values are estimated, Dr. Foreman conducts an analysis of procedure/geozip combinations with 9 claims from “300 common CPT codes for 100 of the most populous geozips using contributor data for 2007 for comparison with 80th percentile values from the PHCS products for 2007 version 1, 2007 version 2, and 2008 version 3.”¹⁵⁸ From these data, Dr. Foreman uses the 32 CPT/geozip combinations with exactly 9 claims in 2007 and tracks the 80th percentile value over the three releases in the analysis. Dr. Foreman concludes from the analysis: “There is large variation in the 80th percentile values from one PHCS product release to another. There are many large increases and large declines – over six month intervals.”¹⁵⁹
160. Dr. Foreman apparently did not consider that a simple explanation for some of large differences he observes is the switching of values from empirical to derived information. Table 28 summarizes the data based on Dr. Foreman’s “Table 14”. Of the 32 observations and 64 possible data changes, there are 39 changes that occur. Of these, there are 14 cases (9 + 2 + 3) that indicate switching from empirical to derived or derived to empirical information. Of these, there are 9 cases (6 + 3) or 64 percent for which the derived amount exceeds the empirical amount. Given my prior results on derived values, Dr. Foreman’s results are not surprising. They are consistent with my findings that PHCS derived values are generally larger than benchmark values for the same procedure/geozip combination. In this case, the benchmark value is the PHCS empirical value.

¹⁵⁸ Based on prior descriptions in his report, I suspect that by “2008 version 3,” Dr. Foreman means 2008 version 1. (In his “Table 14”, he refers to these data as “rel 07.3.”). See Foreman Report at ¶ 247 and “Table 14”. Additionally, in the work product that Dr. Foreman sponsors as support for “Table 14”, he notes the following: “For the subject year 2007, the top 300 procedures represented 79.2% of all procedures performed. An error in joining the Claims to GeoAreas resulted in an arbitrary selection of geozips rather than the actual top 100 for 2007. For consistency, the same method was used for 2006 and 2008; with the plan that all geozips will be processed in the future.” See Buchanan, S.E., “Processes to compare contributor data with Ingenix releases,” Work product supplied by Mr. Frank Cohen on behalf of Dr. Foreman (Jul. 20, 2010).

¹⁵⁹ See Foreman Report at ¶ 249.

Table 28: Switch Between Empirical and Derived Values Influence Results of Foreman Report “Table 14”

	Between 2007.1 & 2007.2	Between 2007.2 & 2008.1
Total CPT/Geozips	32	
Number of CPT/Geozips that change 80th Percentile Value	19	20
Number of CPT/Geozips that switch from Empirical to Derived	9	2
Number of CPT/Geozips that switch from Derived to Empirical	0	3
Number of CPT/Geozips where Empirical > Derived	3	2
Number of CPT/Geozips where Derived > Empirical	6	3
<u>Notes:</u>		
1. Please note that each indentation in this table is a subset of the category above it. For example, the CPT/geozips analyzed for the "Number of CPT/Geozips that switch from Empirical to Derived" row is the set of CPT/geozips that have a change in their 80th percentile value, ie: those represented on the row above, "Number of CPT/Geozips that change 80th Percentile Value".		
2. Source for data: Expert Report of Stephen Foreman (CORRECTED), Ph.D., J.D., M.P.A., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at Table 14. PHCS 2007 releases 1 & 2 and PHCS 2008 release 1.		

c) Further Evidence That Derived Data Generally Exceed Benchmarks

161. I observed previously in the Cantor Responsive Class Certification Report that Plaintiffs' experts have focused a substantial portion of their criticisms of the Ingenix Database on the alleged methodology to estimate derived values.¹⁶⁰ I showed in the Cantor Class Certification Report that derived values account for less than 0.5 percent of the total claim count in the medical and surgical modules of the Ingenix Database. Thus, any conclusions by Plaintiffs' experts about the derived values should not be extended to the Ingenix Database values more generally without substantial further analysis. To address the concerns of Plaintiffs' experts about the derived values, I expanded my benchmark analysis in my Cantor Responsive Class Certification Report to test whether they are systematically and pervasively low compared to the benchmark values. In stark contrast to Plaintiffs' claims and their experts' contentions, my empirical analysis showed that derived values, at least for the medical and surgical procedures in the Ingenix Database, exceed the benchmark values by a wide margin. Based on that analysis and additional

¹⁶⁰ See Cantor Responsive Class Certification Report at ¶ 17. Derived value distributions have fewer than nine occurrences for a given procedure in a given geozip.

work for this report, I conclude derived data percentile values likely exceed external benchmark values.

162. Table 29 expands Dr. Foreman's analysis of derived and empirical values to a much larger dataset. Using both releases on the Ingenix Database over the 2001 to 2007 period, I extracted all cases where there was a switch from derived to empirical or empirical to derived information.¹⁶¹ The table shows that for approximately 53 percent of the cases, the derived values exceed the empirical values. In many of the comparisons reflected in the rows of the table, this proportion exceeds 60 percent.

¹⁶¹ I limited the cases to those for which the empirical claim count was 50 or greater. The derived claim count was less than 9.

Table 29: Results of Switching Between Empirical and Derived Values in Ingenix PHCS Over Time, All CPTs, 2001-2007

Year	Empirical Release	Derived Release	Status	Count of CPT/Geozips	Share
2001	R1	R2	DER < EMP	298	33.8%
			DER > EMP	567	64.3%
			DER=EMP	17	1.9%
	R2	R1	DER < EMP	1,182	36.4%
			DER > EMP	1,984	61.2%
			DER=EMP	78	2.4%
	R1	R2	DER < EMP	405	34.7%
			DER > EMP	739	63.4%
			DER=EMP	22	1.9%
2002	R2	R1	DER < EMP	525	37.3%
			DER > EMP	861	61.1%
			DER=EMP	23	1.6%
	R1	R2	DER < EMP	812	37.1%
			DER > EMP	1,340	61.2%
			DER=EMP	39	1.8%
	R2	R1	DER < EMP	639	54.9%
			DER > EMP	496	42.6%
			DER=EMP	29	2.5%
2003	R1	R2	DER < EMP	259	33.3%
			DER > EMP	505	65.0%
			DER=EMP	13	1.7%
	R2	R1	DER < EMP	2,104	53.4%
			DER > EMP	1,771	44.9%
			DER=EMP	65	1.6%
	R1	R2	DER < EMP	549	39.4%
			DER > EMP	827	59.4%
			DER=EMP	17	1.2%
2004	R2	R1	DER < EMP	1,665	45.1%
			DER > EMP	1,971	53.4%
			DER=EMP	52	1.4%
	R1	R2	DER < EMP	350	29.9%
			DER > EMP	803	68.6%
			DER=EMP	17	1.5%
	R2	R1	DER < EMP	4,600	62.2%
			DER > EMP	2,578	34.9%
			DER=EMP	214	2.9%
2005	R1	R2	DER < EMP	413	30.3%
			DER > EMP	938	68.7%
			DER=EMP	14	1.0%
	R2	R1	DER < EMP	1,569	38.2%
			DER > EMP	2,436	59.4%
			DER=EMP	97	2.4%
	Overall		DER < EMP	15,370	45.4%
			DER > EMP	17,816	52.6%
			DER=EMP	697	2.1%

Notes:

1 To be considered "derived" in this table a CPT/geozip combination must have fewer than 9 claims

2 Only empirical CPT geozip combinations with 50 or greater claims are considered in this analysis

3 Source: PHCS 2001 - 2007

163. To investigate further whether PHCS derived values tend to exceed benchmark values, I purchased the National Fee Analyzer[®] (“NFA”), a commercial benchmark that I understand is based on the MDR data. Dr. Foreman concludes in his report that differences between MDR and PHCS might be due to inflation.¹⁶² He apparently reaches this conclusion because he posits that the relative value normalization used for the derived methodology reduces percentile values.¹⁶³ Dr. Foreman did not consider in his report that despite the derivation methodology, derived values exceed empirical values for the same CPT/geozip combination. I investigate this difference by comparing NFA and empirical and derived values from the Ingenix Database. Table 30 shows the claim-weighted results. When empirical PHCS are compared to derived NFA, the claim weighted percent difference is small but negative. When derived PHCS are compared to NFA, the result is a substantial positive percent difference. The derived values in the Ingenix Database exceed the derived values in NFA. Based on these results, I find that PHCS derived values tend to exceed other benchmark values.¹⁶⁴

Table 30: Claim Weighted Percent Difference Between Ingenix PHCS Derived and Empirical and NFA Average 75th Percentile Values, 2005 & 2006

Year	Status	Percent Difference
2005	Empirical	-3.7%
	Derived	6.1%
2006	Empirical	-3.6%
	Derived	7.0%

Notes:

1. Sources: PHCS Data - Ingenix PHCS 2005 release 2 and Ingenix PHCS 2006 release 2. NFA Data - NFA 2005 and 2006.

164. My analysis continues to support the conclusion that derived values in the Ingenix Database tend to be higher than benchmark values. As a result, there is no foundation based on bias for Plaintiffs to calculate damages for procedure/geozip combinations corresponding to derived data in the Ingenix Database. Table 31 shows that these combinations occur as much as 7 percent of the time in the annual subject Aetna medical and surgical claims and approximately 4 percent overall.

¹⁶² See Foreman Report at ¶ 369.

¹⁶³ See Foreman Report at ¶ 369.

¹⁶⁴ It is also likely that the claim-weighted differences Dr. Foreman finds between MDR and PHCS is due to this derived bias as the claim weighted comparison relies on empirical data for PHCS.

Table 31: Frequency Proportion of Aetna Medical Claims by Distribution of Ingenix Claims, 2001-2008

Year	CPT/Geozip Grouping	Count	Percent
2001	Less Than 9 Claims	5,954	7.0%
	9 to 39 Claims	5,914	6.9%
	40 to 254 Claims	10,942	12.8%
	255 or More Claims	62,371	73.2%
2002	Less Than 9 Claims	122,778	6.3%
	9 to 39 Claims	115,027	5.9%
	40 to 254 Claims	232,445	12.0%
	255 or More Claims	1,473,454	75.8%
2003	Less Than 9 Claims	116,787	6.4%
	9 to 39 Claims	107,995	6.0%
	40 to 254 Claims	229,568	12.7%
	255 or More Claims	1,356,730	74.9%
2004	Less Than 9 Claims	64,210	3.7%
	9 to 39 Claims	72,391	4.2%
	40 to 254 Claims	165,626	9.6%
	255 or More Claims	1,415,358	82.4%
2005	Less Than 9 Claims	42,781	2.6%
	9 to 39 Claims	50,817	3.0%
	40 to 254 Claims	140,748	8.4%
	255 or More Claims	1,439,138	86.0%
2006	Less Than 9 Claims	40,186	2.2%
	9 to 39 Claims	46,522	2.5%
	40 to 254 Claims	122,349	6.7%
	255 or More Claims	1,617,299	88.6%
2007	Less Than 9 Claims	37,936	2.1%
	9 to 39 Claims	43,693	2.4%
	40 to 254 Claims	122,841	6.9%
	255 or More Claims	1,580,637	88.5%
2008	Less Than 9 Claims	36,659	2.1%
	9 to 39 Claims	42,968	2.4%
	40 to 254 Claims	107,778	6.1%
	255 or More Claims	1,579,409	89.4%
Overall			
2001-2008	Less Than 9 Claims	467,291	3.7%
	9 to 39 Claims	485,327	3.8%
	40 to 254 Claims	1,132,297	9.0%
	255 or More Claims	10,524,396	83.5%

Notes:

1. PHCS Data sourced from PHCS 2001-2008.
2. Claim weighted by ACAS 2001-2008 data. Sourced from Excel Files "Aetna200X Medical Damaged Claims.csv" where 200X=2001 through 2008 respectively.

G. Dr. Foreman's Damage Analyses Contain Numerous Errors and Omissions That Substantially Affect His Results

165. My review of Dr. Foreman's methodology, supporting files, and results reveals a number of errors or issues that undermine the basis for and calculations of his final damage figures. Based on my review of the materials provided by Dr. Foreman and my additional analyses, I have three key concerns regarding Dr. Foreman's damage framework and calculations. First, as I discussed in section E.2, he finds a weighted average bias for dental claims that is contrary to my results with a commercial benchmark. When Dr. Foreman's estimated bias is applied to the subject Aetna claims, I find a substantial proportion (on average, 44 to 49 percent) have a billed charge less than his indicated but-for allowed charge. Since Aetna is a large contributor to the Ingenix Database, I find this result peculiar. Dr. Foreman reports no analysis of this result or its cause. Second, Dr. Foreman provides a description of his damage methodology that fails to match his calculations. My analysis of the calculated damages if he had followed his own description for the subject Aetna medical and surgical claims indicates that damages would fall by 66 percent. Third, Dr. Foreman provides insufficient support for his Association damages. More importantly, he has provided no analysis or proof that these damages are justifiable under conditions but for the challenged conduct.

1. Dental Damage Calculations Fail to Support Plaintiffs' Theory

166. Based on his bias analysis, Dr. Foreman concludes that Ingenix percentile values for dental claims are substantially biased downward. His estimates range from 8.2 to 12.3 percent, and his weighted average overall is 9.8 percent.¹⁶⁵ Even when placed on a contemporaneous basis, I found estimates of a negative bias ranging from 4.4 to 8.6 percent using Dr. Foreman's benchmarks. However, my analysis using but not adopting Dr. Foreman's footprint with the only available commercial benchmark showed that any negative bias was trivial (0.3 to 0.8 percent).

167. There is additional information in Dr. Foreman's files supporting his dental damage calculations that raises further questions about his bias results for dental claims. The contributor data indicate that Aetna supplies a substantial proportion of the dental, medical, and surgical claims. Overall, Aetna supplied approximately 20 percent of the contributor data both for dental and medical/surgical categories in Dr. Foreman's 300 Study footprint. Aetna's data therefore should influence the billed charge values in the contributor data and the bias that Dr. Foreman estimates.

¹⁶⁵ See Foreman Report at ¶ 391. These results reflect Dr. Foreman's method of calculating the percent differences.

168. To estimate damages, Dr. Foreman applies either the fixed factor (9.8 percent) or percentile bias factors to the allowed amounts of the subject Aetna dental claims. He then calculates damage as the difference between the billed charge and the "accurate" allowed amount. If billed charge is less than the accurate allowed amount, he limits the damage to the billed amount minus the original allowed amount. This latter case reflects the peculiar result that Dr. Foreman's estimated under-reimbursement exceeds the real world limits. If any purported bias was estimated reliably, then I would not expect a high-proportion contributor of Ingenix data such as Aetna to have many claims that fit in this category.

169. When his estimated bias is applied to the subject Aetna dental claims, however, the results suggest that Aetna does have many claims for which Dr. Foreman's estimates of under-reimbursement exceed the possible limits. The last row in Tables 32 and 33 show that on average, 44 to 49 percent of the subject claims have this issue. In some years, Dr. Foreman's analysis produced the peculiar result more than 50 percent of the time. In contrast, this peculiar result is found approximately 14 percent of the time in Dr. Foreman's damage analysis of the medical and surgical claims.¹⁶⁶

**Table 32: Frequency Proportion of Aetna Dental Claims by Foreman Damage Calculation
Method: Fixed Factor = 9.80, 2001-2008**

Year	Ingenix Occurrences < 255		Foreman "Accurate Allowed" <= Billed Charge		Billed Charge < Foreman "Accurate Allowed"	
	Count	Share	Count	Share	Count	Share
2002	182,799	4%	2,494,203	53%	1,993,520	43%
2003	236,295	4%	2,901,868	53%	2,362,557	43%
2004	636,619	12%	2,623,057	48%	2,212,288	40%
2005	318,600	5%	3,002,690	50%	2,645,152	44%
2006	232,928	4%	3,027,605	51%	2,733,428	46%
2007	-	0%	3,175,077	52%	2,932,573	48%
2008	193,341	3%	2,981,049	50%	2,831,413	47%
Average (2001-2008)	257,226	5%	2,886,507	51%	2,530,133	45%
Average (2002-2006, 2008)	300,097	5%	2,838,412	51%	2,463,060	44%

Notes:

1. Source for claim counts: Excel File "Aetna Dental Corrected.xlsx" tab: "Fixed factor (9.80)"

2. Shares calculated as, e.g., Share of Ingenix Occurrences < 255 = Number of Ingenix Occurrences < 255/Sum of Ingenix Occurrences < 255, Factored Actual Price <= Charge; and Charge < Factored Actual Price.

¹⁶⁶ These results are included in Appendix A.

Table 33: Frequency Proportion of Aetna Dental Claims by Foreman Damage Calculation Method: Percentile Based Factor, 2001-2008

Year	Ingenix Occurrences < 255		Foreman "Accurate Allowed" <= Billed Charge		Billed Charge < Foreman "Accurate Allowed"	
			Count	Share	Count	Share
	Count	Share	Count	Share	Number	Share
2001	-	0%	98,336	51%	95,247	49%
2002	182,799	4%	2,279,794	49%	2,207,929	47%
2003	236,295	4%	2,641,092	48%	2,623,333	48%
2004	636,619	12%	2,381,843	44%	2,453,502	45%
2005	318,600	5%	2,721,099	46%	2,926,743	49%
2006	232,928	4%	2,734,148	46%	3,026,885	50%
2007	-	0%	2,878,933	47%	3,228,717	53%
2008	193,341	3%	2,697,793	45%	3,114,669	52%
Average (2001-2008)	225,073	5%	2,304,130	46%	2,459,628	49%
Average (2002-2006, 2008)	300,097	5%	2,575,962	46%	2,725,510	49%

Notes:

1. Source for claim counts: Excel File "Aetna Dental Corrected.xlsx" tab: "Percentile-based factor"
2. Shares calculated as, e.g., Share of Ingenix Occurrences < 255 = Number of Ingenix Occurrences < 255 / Sum of Ingenix Occurrences < 255, Factored Actual Price <= Charge; and Charge < Factored Actual Price.

170. The dental results should have signaled to Dr. Foreman that more analysis of the alleged bias was warranted. As an economics matter, a finding that such a large proportion of the subject claims falls outside the possible limits of under-reimbursement without further explanation casts doubt on the estimated bias levels.

2. Dr. Foreman's Description of His Damages Methodology Fails to Explain His Calculations

171. Dr. Foreman describes a damage methodology in his report that is not consistent with his table of calculated damages. Notwithstanding my overall concern that Plaintiffs' experts have failed to provide a reliable foundation for any calculation of damages, in this section I show the differences between Dr. Foreman's description and his estimates. Dr. Foreman also calculated damages for years 1998 to 2000, but as I understand Plaintiffs' claims, no damages are due for these years. I exclude these years in my adjustments to the calculations proffered by Dr. Foreman.

172. Dr. Foreman states that he calculates damages using two methods:

[A] measure of damages would be the difference between what Aetna should have paid (billed charge) and what it actually paid (allowed amounts based on Ingenix, less adjustments for deductibles, copayments, coinsurance and coordination of benefits);¹⁶⁷

and

¹⁶⁷ See Foreman Report at ¶ 397.

[A] measure of damages would be the difference between an "accurate" allowed amount and the amounts paid.¹⁶⁸

Dr. Foreman claims that in the second method "damages relate to a 'but for' world where the percentile values are accurate ones and replace the Ingenix percentile values used in the past by Aetna with the accurate 80th values to produce accurate allowed amounts."¹⁶⁹

- 173. My analysis of Dr. Foreman's estimated damages indicates that he is not applying his description of the second method above. In Table 34, I reproduce Dr. Foreman's medical and surgical estimates and correct one apparent arithmetic error. The corrected value of his estimate is approximately \$728 million.
- 174. In Table 35, I show the results when damages are limited to Dr. Foreman's stated intent to measure a difference between accurate allowed and allowed. I also remove the years 1998 to 2000 from the estimates. Under these conditions, Dr. Foreman's damage estimate falls to approximately \$245 million—a 66 percent reduction in the corrected estimate.

Table 34: Foreman "Table 36", Modified

A	B	C	C-B/B <i>Percent Difference between Allowed</i>	D	D/B	E	F	D/B * E
<i>Charges Billed</i>	<i>Allowed</i>	<i>Accurate Allowed</i>	<i>and Accurate Allowed</i>	<i>Paid</i>	<i>Percent Paid</i>	<i>Prelim. Est.</i>	<i>Foreman Final Est.</i>	<i>Corrected Foreman Final Estimate</i>
2010 \$298,480,080	\$184,729,833	\$205,511,939	<i>11.25%</i>	\$118,229,051	64.0%	\$48,787,280	\$33,946,074	\$31,223,859
2009 \$596,960,161	\$369,459,665	\$411,023,879	<i>11.25%</i>	\$236,458,101	64.0%	\$97,574,560	\$67,892,148	\$62,447,718
2008 \$596,960,161	\$369,459,665	\$411,023,879	<i>11.25%</i>	\$236,458,101	64.0%	\$97,574,560	\$67,892,148	\$62,447,718
2007 \$552,712,954	\$355,592,072	\$395,596,181	<i>11.25%</i>	\$228,513,491	64.3%	\$87,147,788	\$61,186,539	\$56,036,028
2006 \$528,881,444	\$347,621,152	\$386,728,532	<i>11.25%</i>	\$227,542,215	65.5%	\$82,371,100	\$58,332,611	\$53,953,071
2005 \$478,322,265	\$318,053,057	\$353,834,028	<i>11.25%</i>	\$213,089,860	67.0%	\$76,341,523	\$54,945,402	\$51,148,820
2004 \$473,668,745	\$318,696,781	\$354,550,170	<i>11.25%</i>	\$219,399,182	68.8%	\$81,005,687	\$59,595,027	\$55,731,913
2003 \$482,813,739	\$327,112,940	\$363,913,147	<i>11.25%</i>	\$233,908,362	71.5%	\$80,934,445	\$61,830,620	\$57,868,128
2002 \$463,213,149	\$317,478,220	\$353,194,522	<i>11.25%</i>	\$232,759,415	73.3%	\$81,049,977	\$63,165,002	\$59,409,633
2001 \$463,213,149	\$317,478,220	\$353,194,522	<i>11.25%</i>	\$232,759,415	73.3%	\$81,049,977	\$63,165,002	\$59,409,633
2000 \$463,213,149	\$317,478,220	\$353,194,522	<i>11.25%</i>	\$232,759,415	73.3%	\$81,049,977	\$63,165,002	\$59,409,633
1999 \$463,213,149	\$317,478,220	\$353,194,522	<i>11.25%</i>	\$232,759,415	73.3%	\$81,049,977	\$63,165,002	\$59,409,633
1998 \$463,213,149	\$317,478,220	\$353,194,522	<i>11.25%</i>	\$232,759,415	73.3%	\$81,049,977	\$63,165,002	\$59,409,633
<i>Foreman's Total Final Est.</i>							\$781,445,576	\$727,905,421
<i>Actual Sum of Foreman Final Est. Column</i>							\$781,445,579	

Notes:

1 Italics indicate columns added to original table

2 Data sourced from the PDF File "Foreman Report Corrections pdf" at Table 36

¹⁶⁸ See Foreman Report at ¶ 398.

¹⁶⁹ See Foreman Report at ¶ 415.

Table 35: Foreman “Table 36” Corrected

A	B = A*[1.1125]	C = B-A	D	C*D	
	Allowed	Accurate Allowed	Prelim. Est.	Percent Paid	Corrected Final Estimate
2010	\$184,729,833	\$205,511,939	\$20,782,106	64.0%	\$13,300,548
2009	\$369,459,665	\$411,023,877	\$41,564,212	64.0%	\$26,601,096
2008	\$369,459,665	\$411,023,877	\$41,564,212	64.0%	\$26,601,096
2007	\$355,592,072	\$395,596,180	\$40,004,108	64.3%	\$25,722,642
2006	\$347,621,152	\$386,728,532	\$39,107,380	65.5%	\$25,615,334
2005	\$318,053,057	\$353,834,026	\$35,780,969	67.0%	\$23,973,249
2004	\$318,696,781	\$354,550,169	\$35,853,388	68.8%	\$24,667,131
2003	\$327,112,940	\$363,913,146	\$36,800,206	71.5%	\$26,312,147
2002	\$317,478,220	\$353,194,520	\$35,716,300	73.3%	\$26,180,048
2001	\$317,478,220	\$353,194,520	\$35,716,300	73.3%	\$26,180,048
Total Final Est. \$ 245,153,337					

Notes:

1. Allowed and Percent Paid are sourced from the PDF File "Foreman Report Corrections.pdf" at Table 36.
2. Reflects 2001-2010 damage period.

175. Subsequent production materials from Dr. Foreman, but authored by Mr. Frank Cohen, indicate that damages for procedure/geozip combinations with less than 255 claims were not estimated according to Dr. Foreman’s second method. Instead the first method—billed charge minus allowed amount—apparently was used in both methods. Dr. Foreman reports no justification for this substitution and it appears contrary to his statement that “the court might determine that use of percentile data for determining UCR would be appropriate if more accurate data were used in which event it could determine that an ‘accurate allowed charge’ amount would provide the best measure of damages.”¹⁷⁰ Based on Dr. Foreman’s proffered numbers, this option has been removed from the Court’s prerogative for procedure/geozip combinations with less than 255 claims.¹⁷¹

¹⁷⁰ See Foreman Report at ¶ 396.

¹⁷¹ Dr. Foreman admits in his deposition that he has removed this from the Court’s decision by testifying that “it would not be appropriate to [apply the 11.2 percent accurate allowed adjustment factor to claim lines in geo zips with less than 255 observations] given that there would be insufficient counts in those CPT geo zip combinations to use a percentile methodology.” (See Foreman Merits Deposition Volume I at pp. 281:17-282:4).

3. Dr. Foreman Provides No Foundation or Work Product for the Named Association Damages

176. Dr. Foreman calculates damages for the Association Plaintiffs, but he provides no detailed analysis or foundation for these calculations.¹⁷² Notably, he provides no detailed support of his “informal survey of the Association plaintiffs.”¹⁷³ He does not identify in his report which Associations he surveyed, how he surveyed them, questions he asked, or how he validated the responses. Without these basic supporting materials, the rigor of Dr. Foreman’s approach and the reliability of his data cannot be evaluated.

177. I note that some of the salary amounts reported by Dr. Foreman appear suspect when compared to publicly available information. For example, Dr. Foreman reports an annual salary for the director of the Florida Medical Association that is \$624,000. A comparable 75th percentile value for such a position is approximately \$148,164.¹⁷⁴ Other estimates of Association senior positions are much more consistent with the publicly available data.¹⁷⁵

178. Without further explanation or analysis, Dr. Foreman reports the time and costs of the Association Plaintiffs apparently due to ONET transaction costs. He provides no analysis to confirm that these values are truly incremental and that the time and professionals described would be unnecessary in the world but for the challenged conduct. Dr. Foreman provides no evidence of any study to support that time spent on claim adjudication with the Defendants is wholly incremental to time spent with non-Defendant

¹⁷² In the work products supporting his report, Dr. Foreman includes an Excel file, “AssociationDamagesInfo.xls” (and replicas in Adobe PDF by the same name) that appears to include some of the values that are in his report, but provides no supporting documentation for those values.

¹⁷³ See Foreman Report at ¶ 458. During his deposition, Dr. Foreman testified that he did not perform the survey himself. Rather, he asked plaintiffs’ legal counsel to perform the survey for him.

Q. Okay, in paragraph 472, you write that in order to estimate association plaintiff damages, we conducted an informal survey of the association plaintiffs. Who is the “we”?

A. I asked legal counsel at [Whatley Drake & Kallas] to contact their client contacts at each of the associations and to inquire of them their estimate [...] of personnel time and expenses incurred dealing with the issue of out of network improper out of network claims (sic).

[...]

Q. Did you provide questions to counsel that they were to ask the association representatives?

A. I did not. I described the concept.

[...]

A. The concepts, I inquired – [...] I am not sure as we sit here the specific terminology that we used, but the concept was that the association time and expense were for those activities that were incurred in connection with out of network claim processing using Ingenix.

See Foreman Merits Deposition Volume II at pp. 176:8 – 181:7.

¹⁷⁴ To gather estimates for similar positions, I directed my staff to access sites such as Salary.com, which provides national estimates for the 25th percentile and 75th percentile of various positions. A search for “chief association executive” found that these values were \$161,209 and \$313,294. For director, comparable values were \$99,484 and \$148,164. See Attachment 3 for the website references.

¹⁷⁵ For examples, Dr. Foreman reports that the director’s salary at the New Jersey Psychological Association is \$81,818, and the executive’s salary at the American Medical Association is \$200,000.

managed care providers. Some of the descriptions provided by Dr. Foreman regarding the categories of costs incurred appear inconsistent with a proper incremental analysis. For example, Dr. Foreman reports: “[t]he Connecticut State Medical Society has incurred \$410,000 for staff, consultants, outside counsel and *lobbyists*.¹⁷⁶ Without a proper analysis of costs that would not exist under the but-for conditions, Dr. Foreman’s calculations are speculative.

V. Conclusions

179. Plaintiffs’ experts have not provided independent or reliable analysis sufficient to alter my original findings that the Ingenix Database is not systematically biased downward across the board or on average. Plaintiffs’ experts have failed to show that the alleged data collection and compilation flaws of the Ingenix Database cause a systematic downward bias. Using, but not adopting, Dr. Foreman’s sponsored 300 and 350 Studies as benchmarks fails to contradict my original analysis which addressed all or nearly all empirical and derived medical, surgical, and dental Ingenix procedure/geozip combinations.
180. Dr. Foreman’s 300 and 350 Studies, however, are unsuitable benchmarks due to serious and pervasive data and processing errors. In addition, his benchmarks contain less than one percent of the procedure/geozip combinations that he identifies as relevant in this matter. Dr. Foreman has not even attempted to prove that his results can be generalized to the entire database that Plaintiffs allege is biased downward. His claim-weighted results cannot be extrapolated to the substantial majority of combinations not examined without further consideration of the representativeness of his limited footprints.
181. Plaintiffs’ experts fail to test whether the Ingenix Database compilation and construction procedures are routine industry practices used to manage large databases. Such an assessment is critical for their bias and damage analyses because Plaintiffs have alleged that these practices are the “end result” of “cycle of collusion” among Defendants. Information about industry practices addresses directly whether or not such procedures likely would be used but for the challenged conduct. My review of automated scrubbing rules for outliers, data pooling, and voluntary contribution of data by contributors indicates that the Ingenix procedures are consistent with industry practices to manage very large databases.
182. In addition, Plaintiffs’ experts have not met their burden to demonstrate that the Ingenix Database methodology suppresses percentile values and causes injuries to members of the proposed Class. Regarding the alleged flaws, they show no bias for representativeness. A generalized proof of the high-low screen shows that it can reduce, increase, or leave unchanged percentile values depending on factors defining the original and combined billed-charge distributions. Derived data generally exceed any other

¹⁷⁶ See Foreman Report at ¶ 458.

benchmark values. Plaintiffs' experts fail to show bias related to provider specialties, different places of service, modifiers, or the use of geozips to organize the billed charge data. As Plaintiffs' experts have not proved that the Ingenix methodology causes percentile values to be suppressed, they have failed to provide a foundation for their damage analysis and subsequent calculations.



Robin Cantor
November 10, 2010

APPENDIX A: ADDITIONAL ANALYSES

This appendix presents additional analyses that accompany results presented in the report.

Dr. Foreman's 300 and 350 footprints are correlated with commercial and government benchmarks

As noted in paragraph 122 of my report, the percentile values in Dr. Foreman's 300 and 350 footprints follow the same general patterns as the commercial and government benchmarks and PHCS for the limited set of procedure/geozip combinations that he investigates. Tables A-1 and A-2 report the correlation results between Dr. Foreman's benchmarks, the commercial and government benchmarks, and PHCS for medical and surgical procedures in 2006 and 2007, respectively. The correlations for 2006 generally are the highest and most consistent across comparisons. The decline in correlation that is observed for 2007 might be an indication of errors in the compiled Foreman benchmarks, discussed in section [] of my report.

Table A-3 reports the correlation for dental procedures in 2007.¹ Dr. Foreman's footprint is highly correlated with the comparable data in both the Wasserman (PFR) benchmark and PHCS.

¹ Only Dr. Foreman's 300 Study includes dental procedures.

Table A-1: Correlations Between Foreman's Benchmark and Commercial Benchmarks - 2006

Comparison		Correlation
Benchmark	Foreman 300 Footprint	
PFR 75 th Percentile	75 th Percentile	0.944
PFR 90 th Percentile	90 th Percentile	0.909
PMIC 75 th Percentile	75 th Percentile	0.937
MAG High	85 th Percentile	0.923
Medicare PSPS Mean	Mean	0.915
PHCS 75 th Percentile	75 th Percentile	0.967
PHCS 80 th Percentile	80 th Percentile	0.957
PHCS 85 th Percentile	85 th Percentile	0.942
PHCS 90 th Percentile	90 th Percentile	0.921
PHCS Mean	Mean	0.975

Comparison - 2006 First Six Months ⁴		Correlation
Benchmark	Foreman 350 Footprint	
PFR 75 th Percentile	75 th Percentile	0.939
PFR 90 th Percentile	90 th Percentile	0.892
PMIC 75 th Percentile	75 th Percentile	0.931
MAG High	85 th Percentile	0.911
PHCS 75 th Percentile	75 th Percentile	0.959
PHCS 80 th Percentile	80 th Percentile	0.949
PHCS 85 th Percentile	85 th Percentile	0.932
PHCS 90 th Percentile	90 th Percentile	0.907

Comparison - 2006 Second Six Months ⁴		Correlation
Benchmark	Foreman 350 Footprint	
PFR 75 th Percentile	75 th Percentile	0.940
PFR 90 th Percentile	90 th Percentile	0.893
PMIC 75 th Percentile	75 th Percentile	0.932
MAG High	85 th Percentile	0.911
PHCS 75 th Percentile	75 th Percentile	0.959
PHCS 80 th Percentile	80 th Percentile	0.949
PHCS 85 th Percentile	85 th Percentile	0.932
PHCS 90 th Percentile	90 th Percentile	0.907

Notes:

1 P-value < 0.0001 for all correlations

2 Source for Foreman contributor percentiles, 300 Footprint 2006: Comp 300 Ing_06_01.xlsx

Source for Ingenix percentiles: Ingenix PHCS, 2006 second release

3 Source for Foreman contributor percentiles, 350 Footprint 2006:

Compare_Contrib_2006_1.xlsx

Source for Ingenix percentiles: Ingenix PHCS, 2006 releases 1 & 2

4 "2006 - First Six Months" and "2006 - Second Six Months" refer to the range of time spanned by the contributor data reportedly used by Dr. Foreman

Table A-2: Correlations Between Foreman's Benchmark and Commercial Benchmarks - 2007

Comparison		Correlation
Benchmark	Foreman 300 Footprint	
PFR 75 th Percentile	75 th Percentile	0.887
PFR 90 th Percentile	90 th Percentile	0.825
Medicare PSPS Mean	Mean	0.935
PHCS 75 th Percentile	75 th Percentile	0.919
PHCS 80 th Percentile	80 th Percentile	0.897
PHCS 85 th Percentile	85 th Percentile	0.875
PHCS 90 th Percentile	90 th Percentile	0.847
Ingenix Mean	Mean	0.950

Comparison		Correlation
Benchmark	Foreman 350 Footprint	
PFR 75 th Percentile	75 th Percentile	0.841
PFR 90 th Percentile	90 th Percentile	0.595
Medicare PSPS Mean	Mean	0.806
PHCS 75 th Percentile	75 th Percentile	0.886
PHCS 80 th Percentile	80 th Percentile	0.836
PHCS 85 th Percentile	85 th Percentile	0.746
PHCS 90 th Percentile	90 th Percentile	0.627
Ingenix Mean	Mean	0.855

Notes:

1. P-Value< 0.0001
2. Source for Foreman contributor percentiles, 300 Footprint: Comp 300 Ing_07_02 Rev.xlsx - med surg07 tab. Source for Ingenix percentiles: Ingenix PHCS, 2007 second release.
3. Source for Foreman contributor percentiles, 350 Footprint: Compare_Contrib_2007_1.xlsx. Source for Ingenix percentiles: Ingenix PHCS, 2007 release 2.

Table A-3: Correlations Between Foreman Benchmark and Commercial Benchmarks for Dental Procedure Codes – 2007

2007		
Comparison		Coefficient
Benchmark	Foreman 300 Footprint	
NDAS 80 th Percentile	80 th Percentile	0.984
PHCS 80 th Percentile	80 th Percentile	0.999

Notes:

1. P-Value< 0.0001
2. Source for Foreman contributor percentiles, 300 Footprint: Excel File "Comp 300 Ing_07_02 Rev.xlsx" tab "dental07". Source for Ingenix percentiles: PHCS 2007 release 2.

Analysis of provider specialty and place of service

Despite sponsoring the opinion that “Empirical analysis using health insurance firm and contributor data shows that billed charges (for the same CPT code) differ substantially and significantly among different providers and specialties,” Dr. Foreman offers no analysis in his report of whether specialty or place of service biases the PHCS database downward.² The contributor data includes fields for these characteristics but they are not sufficiently populated to enable a reliable analysis. However, the Medicare PSPS database does provide sufficient information to analyze the implications of these characteristics for average billed charges. Using the Medicare PSPS database for 2006, I examined the percent difference in average fees for place of service and provider specialty relative to the overall average by CPT, carrier and locality. Table A-4 reports that more than half the time, the overall average fee is greater than or equal to that for the place of service or provider specialty. In fact, the claim weighted average percent difference indicates that the overall average is 2.1% *higher* than the average specific to a place of service. The overall average is 4.5% *higher* than averages for separate provider specialties. These results indicate that further separation of the data for place of service or provider specialty factors is not likely to increase percentile values for billed charges across the board or on average.

² See Foreman Report at ¶ 17. In his deposition, Dr. Foreman admits that this analysis is not in his report and agrees that he would “withdraw this bullet point from [his] report.” (See Foreman Merits Deposition Volume I at pp. 80:3 – 81:25).

Table A-4: Medicare PSPS 2006 - Specialty and Place of Service Analysis

Frequency Proportions for Percent Difference in Average Fees: Place of Service/Specialty Relative to Overall Average			Percent Difference Analysis: Overall Average Relative to Place of Service/Specialty
	Frequency Greater Than Zero - Simple Average	Frequency Equal To Zero - Simple Average	Frequency Less Than Zero - Simple Average
Place of Service	42.9%	15.7%	41.5%
Specialty	49.8%	3.5%	46.7%

Notes:

1. Percent difference of each specialty calculated as $(\text{Overall Average} - \text{Specialty Average}) / (\text{Specialty Average})$. The same formula is applied to calculate the percent difference for each place of service. These calculations are performed by CPT, carrier and locality and are limited to place or service or specialty with claim count greater than 30.
2. Claim weighted by Medicare PSPS 2006 claim count by CPT, carrier and locality.
3. Source: Medicare PSPS 2006 Master File.

Analysis of Aetna medical/surgical claims under Foreman's "accurate allowed" damages estimation method

To estimate damages, Dr. Foreman reports that he applies a fixed factor of 11.2 percent to the allowed amounts of the subject Aetna medical and surgical claims under his "accurate allowed" damages estimation method. He then calculates damage as the difference between the billed charge and the "accurate" allowed amount. If the billed charge is less than the "accurate" allowed amount, he limits the damage to the billed amount minus the original allowed amount. The last row of Table A-5 shows that on average, 14 percent of the subject claims have this issue.

Table A-5: Frequency Proportion of Aetna Medical/Surgical Claims by Foreman Damage Calculation Method: Fixed Factor = 11.2, 2001-2008

Year	PHCS Occurrences <		Foreman "Accurate Allowed" <= Billed Charge		Billed Charge < Foreman "Accurate Allowed"	
	255		Count	Share	Count	Share
	Count	Share	Count	Share	Count	Share
2001	-	0%	69,190	82%	15,127	18%
2002	321,812	17%	1,363,073	71%	248,465	13%
2003	259,722	14%	1,345,759	72%	262,830	14%
2004	263,548	15%	1,277,267	72%	245,327	14%
2005	229,151	13%	1,264,413	73%	242,784	14%
2006	172,892	9%	1,437,621	77%	262,327	14%
2007	153,344	8%	1,451,090	78%	251,051	14%
2008	148,506	8%	1,422,419	79%	234,256	13%
Average (2001-2008)	193,622	12%	1,203,854	74%	220,271	14%
Average (2002-2006)	249,425	14%	1,337,627	73%	252,347	14%

Notes:

1. Source for claim counts: Excel File "Aetna Medical Corrected.xlsx" tabs: 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008.
2. Shares calculated as, for example, "Share of PHCS Occurrences < 255" = "Count of PHCS Occurrences < 255" / ("Count of PHCS Occurrences < 255" + "Foreman 'Accurate Allowed' <= Billed Charge" + "Billed Charge < Foreman 'Accurate Allowed'").

APPENDIX B: EXAMPLES OF FEDERAL & INTERNATIONAL LARGE DATABASE MANAGEMENT RULES

Database Name	Organization	Organization Level	Document Title & Page #	Automatic Outlier Rule?	Rule Type	Rule Summary	Rule Detail
Kids' Inpatient Database (KID)	Healthcare Cost and Utilization Project (HCUP)	Federal-State Agency Partnership	HCUP Kids' Inpatient Database Design Report, 1997 (p 18)	Spread	There exists an outlier threshold above the 75th percentile and below the 25th percentile Does not discard outliers	"The shaded area of each box is bounded below by the 25th percentile and is bounded above by the 75th percentile. The white line within the shaded area marks the median (50th percentile). The thin lines extending from the top and bottom of the boxes extend to upper and lower outlier thresholds, respectively. The horizontal lines drawn above and below the outlier thresholds mark the locations of the outliers themselves "	
The World Health Organization Global Database on Child Growth and Malnutrition	World Health Organization (WHO)	International/Global	The World Health Organization Global Database on Child Growth and Malnutrition: Methodology and Applications, 2003, (p 519)	Spread ✓	Survey data are checked for inconsistencies Edits focus particularly on accuracy of age reporting by using the standard dev of the z-score distribution to gauge the data quality, e.g., data with incorrect age reporting is excluded	"As part of routine data quality control, survey results are checked for inconsistencies. The observed standard deviations (SD) of the z-score distribution are used to assess the quality of the survey data. With accurate age estimates and anthropometric measurements, the SD of the observed z-score distributions should be relatively constant and close to the expected value of 1.0 for the reference distribution (ranging within approximately 0.2 units). Surveys with obvious inaccurate data resulting from measurement error or incorrect age reporting are generally excluded"	
Consolidated Human Activity Database (CHAD)	Environmental Protection Agency (EPA)	Federal	CHAD User's Guide, March 22, 2002 (p 44) Teleconference with Thomas McCurdy - EPA - re CHAD Data - 6 24 10	Spread ✓	Top and bottom 5% were cut off the normal, lognormal or exponential distribution	LTail = percent of the distributions left tail to cut off RTail = percent of the distribution's right tail to cut off 5% are automatically cut off in the case of normal, lognormal or exponential distribution (based on a conversation with Mr. Thomas McCurdy, Exposure Modeling Research Branch, EPA; Email: mccurdy.thomas@epa.gov)	
Medical Expenditure Panel Survey (MEPS)	U.S. Department of Health and Human Services, Agency for Healthcare Research and Quality (AHRQ)	Federal-State Agency Partnership	Moeller JF, Stagnitti MN, Horan E, et al. Outpatient Prescription Drugs: Data Collection and Editing in the 1996 Medical Expenditure Panel Survey (HC-010A), Rockville (MD): Agency for Healthcare Research and Quality; 2001. MEPS Methodology Report 12, AHRQ Pub No 01-0002 (p 12)	Automatic Multiple ✓	If the retail unit price was less than 80% of average wholesale price, the retail unit price was increased to the AWUP	Rule P9: "This edit identified cases in which the RUP [retail unit price] was under 80 percent of the AWUP [average wholesale unit price]. In the edit the RUP was increased to the AWUP."	
<i>Ibid.</i>	<i>Ibid.</i>	<i>Ibid.</i>	<i>Ibid.</i> (pp 12-13)	Automatic Multiple ✓	In the event that the retail unit price was 10 times (or 20 times prior to 1996) higher than the average wholesale unit price of the drug, the retail unit price was reduced to the average wholesale unit price	Rule P11: "In these cases, the reported RUP of the drug equaled or exceed 10 times the AWUP (or 20 times the AWUP if the AWUP was measured before 1996). In the edit, the reported RUP was reduced to the AWUP."	
American Community Survey (ACS)	U.S. Census Bureau	Federal	ACS Design and Methodology Chapter 10: Data Preparation and Processing for Housing Units and Group Quarters (pp 10-2, 10-3)	Logical Consistency ✓	Computerized checks for sufficient responses and size of household are applied to data received by mail. Illegal responses are edited to legal ones	"Data received by mail are run through a computerized process... During creation of the DCF [Data Capture File], responses are reviewed and illegal values responses are identified. Data capture rules cause some variables to be changed from illegal values to legal values, e.g., a respondent leaves a date of birth blank but gives 'Age' as 125. This value is above the maximum allowable value of 115. This variable would be recorded as 115."	
2009 Youth Risk Behavior Survey (YRBS)	U.S. Department of Health and Human Services, Centers for Disease Control and Prevention (CDC)	Federal	2009 National YRBS Data Users Manual, (pp 3; 5)	Spread Logical Consistency	Checks for range, height/weight plausibility, logical consistency. Invalid data set to missing BMI calculated to check height/weight, data excluded if deemed invalid	"Editing consists of checking responses for range, height/weight plausibility, and logical consistency. Data deemed invalid are set to missing... When the basic edits for BMI are complete, further edits are applied to Height, Weight, and BMI to ensure the results are biologically plausible. Height, Weight, and BMI are set to missing when an observation lies outside the limits developed by the Division of Nutrition, Physical Activity and Obesity, CDC."	
Medical Expenditure Panel Survey (MEPS)	Agency for Healthcare Research and Quality (AHRQ), Center for Financing, Access, and Cost Trends	Federal-State Agency Partnership	MEPS HC-105: 2006 Full Year Consolidated Data File, November 2008 (p C-107)	Pooling	Multiple years of data are pooled to create sample sizes large enough to analyze for less common events (Note: Appears multiple times in different MEPS documents)	"To facilitate analysis of subpopulations and/or low prevalence events, it may be desirable to pool together more than one year of data to yield sample sizes large enough to generate reliable estimates. For each data year preceding 2002 that is being pooled, it is necessary to obtain appropriate strata and psu variables for variance."	

APPENDIX B: EXAMPLES OF FEDERAL & INTERNATIONAL LARGE DATABASE MANAGEMENT RULES

Ibid.	Ibid.	MEPS HC-105: 2006 Full Year Consolidated Data File, November 2008 (p C-100)	Pooling	Data are pooled by payment source, e.g., Medicare, Medicaid, Private Insurance, etc	[V]ariables are provided that itemize expenditures according to the major source of payment categories. These categories are: 1 Out of pocket by patient or patient's family (SLF); 2 Medicare (MCR); 3 Medicaid (MCD); 4 Private Insurance (PRV); 5 Veterans' Administration, excluding CHAMPVA (VA); 6 TRICARE (TRI); 7 Other Federal Sources--includes Indian Health Service, Military Treatment Facilities, and other care provided by the Federal government (OFD); 8 Other State and Local Source--includes community and neighborhood clinics, State and local health departments, and State programs other than Medicaid (STL); 9 Worker's Compensation (WCP); 10 Other Unclassified Sources--includes sources such as automobile, homeowner's, liability, and other miscellaneous or unknown sources (OSR) 11 Other Private (OPR) - any type of private insurance payments reported for persons not reported to have any private health insurance coverage during the year as defined in MEPS (i.e., for hospital and physician services); and 12 Other Public (OPU) - Medicaid payments reported for persons who were not reported to be enrolled in the Medicaid program at any time during the year "
National Health Interview Survey (NHIS)	U.S. Department of Health and Human Services, Centers for Disease Control and Prevention (CDC)	Federal	National Health Interview Survey: CAPI Manual for NHIS Field Representatives, HIS-100C, January 2007 (p C-27)	Pooling	Data collected on medical conditions are pooled into preset categories given to the respondent when the question is asked "What conditions or health problems cause {subject name's} limitations? This question is asked both for children and adults. Each contains a single screen of item responses. For children, Flashcard (F1) lists 13 conditions and health problems. For adults, Flashcard (F2) lists the conditions and health problems for the first 18 categories listed on the screen "
Kids' Inpatient Database (KID)	Healthcare Cost and Utilization Project (HCUP)	Federal-State Agency Partnership	HCUP Kids' Inpatient Database Design Report, 1997, (p 2)	Pooling	Survey pools data by geographic region, type of hospital (e.g., government non-federal), urban or rural, teaching status and bed size (number of beds available) prior to weighting data for estimate calculation For the purposes of calculating discharge weights, we post-stratified hospitals on six characteristics contained in the AHA hospital files. The stratification variables were as follows: 1) Geographic Region – Northeast, Midwest, West, and South. This is an important stratifier because practice patterns have been shown to vary substantially by region. For example, lengths of stay tend to be longer in East Coast hospitals than in West Coast hospitals. 2) Control – government nonfederal, private not-for-profit, and private investor-owned. These types of hospitals tend to have different missions and different responses to government regulations and policies. 3) Location – urban or rural. Government payment policies often differ according to this designation. Also, rural hospitals are generally smaller and offer fewer services than urban hospitals. 4) Teaching Status – teaching or nonteaching. The missions of teaching hospitals differ from nonteaching hospitals. In addition, financial considerations differ between these two hospital groups. A hospital is considered to be a teaching hospital if it has an AMA-approved residency program or is a member of the Council of Teaching Hospitals (COTH). 5) Bedsize – small, medium, and large. Bedsize categories are based on hospital beds, and are specific to the hospital's location and teaching status, as shown in Table 1.

APPENDIX C: ANALYSIS OF MAG MUTUAL HIGH VALUE

MAG Mutual (“MAG”) publishes a commercial product called *Physicians Fee & Coding Guide*. This reference source does not provide fee values at percentile levels. Rather, MAG reports a Low and High value. Responding to a request from Defendants in this matter, MAG produced a file called “2010_Final_Fees_Master.xls” (“Master File”). My staff confirmed with MAG representatives that this file includes examples of fee values by CPT code at various percentile levels for 2005 and 2006. These fee values were provided to MAG by independent data contributors, which MAG used in its analysis to establish the MAG Fee Range in 2005 and 2006, respectively.¹ MAG representatives noted that the data provided for 2005 and 2006 were from two different contributors. This appendix explains the analysis of the 2005 and 2006 percentile data in the Master File which was used to estimate the percentile most closely represented by the MAG High value.

The Master File contains pricing and other information for listed CPTs from two independent data contributors, including the percentile distribution for 2005 and 2006.² The MAG Mutual *Physician’s Fee and Coding Guide* of 2005 and 2006 (MAG 2005, MAG 2006) were matched to the Master File by CPT. For the comparison, each 2005 and 2006 percentile of the Master file was compared to the value of the High fee reported by MAG in 2005 or 2006, respectively.

Although highly correlated with all percentile values, the summary statistics and graphical representation of the data indicate that MAG 2005 High and MAG 2006 High match the values of the 85th or 90th percentile provided by contributors to MAG best. As seen in Tables C1 and C2, the median average percent difference is smaller for the 85th and 90th percentiles compared to the other percentiles listed.³ Figures C-1 and C-2 compare the log of the MAG High fee value to the log of the percentile values provided by the data contributors. These figures demonstrate that the level in the MAG High value appears to be centered in the 85th percentile best, relative to the 80th, 90th, or 95th percentile values.

¹ MAG did not reveal the formula used to estimate its Low and High values or the identity of the two independent data contributors.

² Percentiles in the file include the 10th, 25th, 50th, 65th, 75th, 80th, 85th, 90th, 95th, and 100th. The file also includes Medicare data.

³ For the percentiles not reported in the table, the median average percent difference deviates further from the 85th percentile in either direction.

Table C1: Percent Difference Analysis: MAG High Fee Value versus MAG Independent Data Contributor, 2005

Comparison	Average Percent Difference	
	Mean	Median
MAG High 65th Percentile	172.5%	23.9%
MAG High 75th Percentile	226.2%	11.6%
MAG High 80th Percentile	220.5%	6.3%
MAG High 85th Percentile	214.8%	0.9%
MAG High 90th Percentile	207.3%	-5.9%
MAG High 95th Percentile	201.1%	-13.7%

Note:

1. Sources: MAG Mutual, 2005, “2010_Final_Fees_Master.xls”
2. Percent difference calculation: (MAG High Fee Value – Data Contributor Percentile Value)/Data Contributor Percentile Value)

Table C2: Percent Difference Analysis: MAG High Fee Value versus MAG Independent Data Contributor, 2006

Comparison	Average Percent Difference	
	Mean	Median
MAG High 65th Percentile	187.3%	31.2%
MAG High 75th Percentile	135.4%	17.2%
MAG High 80th Percentile	123.7%	11.0%
MAG High 85th Percentile	112.4%	3.5%
MAG High 90th Percentile	102.4%	-4.4%
MAG High 95th Percentile	91.2%	-14.3%

Note:

1. Sources: MAG Mutual, 2006, “2010_Final_Fees_Master.xls”
2. Percent difference calculation: (MAG High Fee Value – Data Contributor Percentile Value)/Data Contributor Percentile Value)

Figure C1: Comparison of MAG High Fee Value to Percentile Values from a MAG Independent Data Contributor, 2005

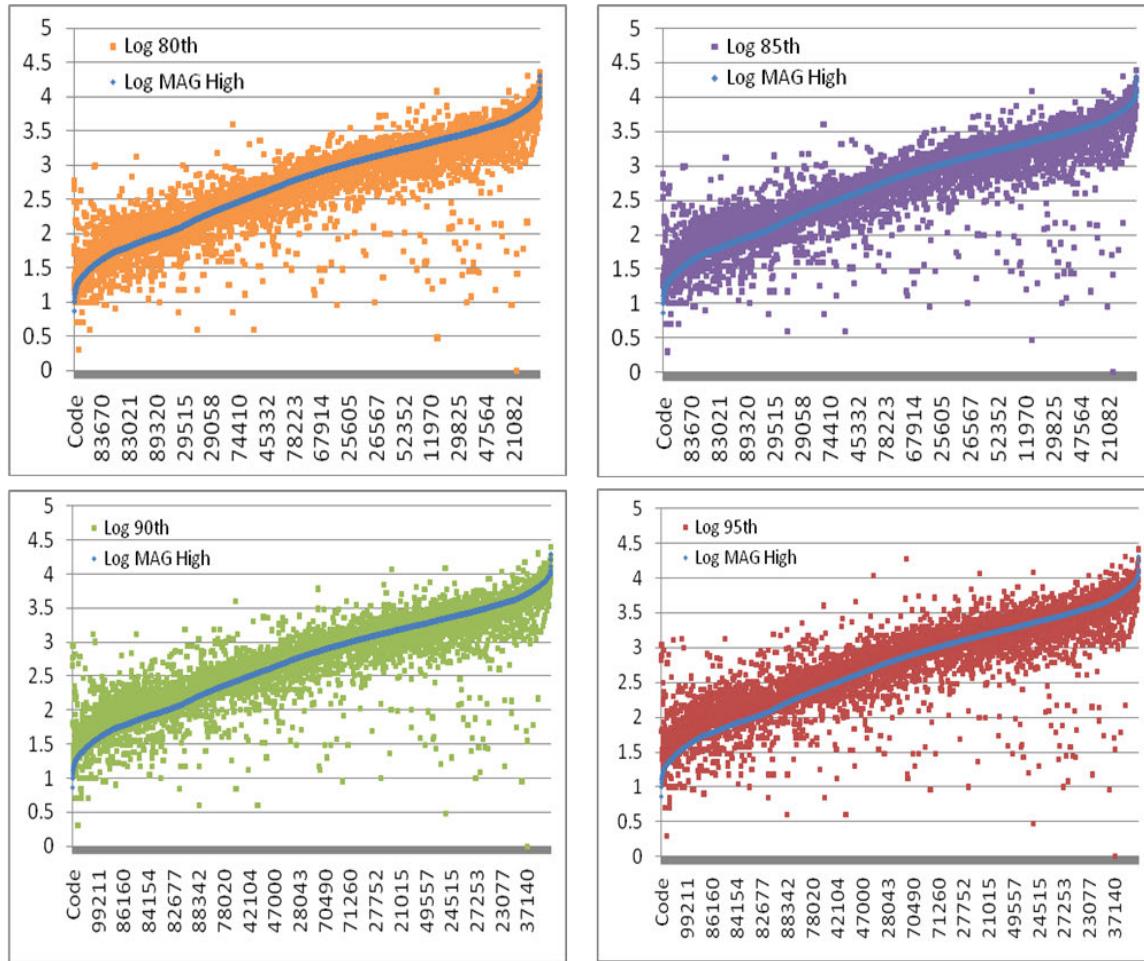
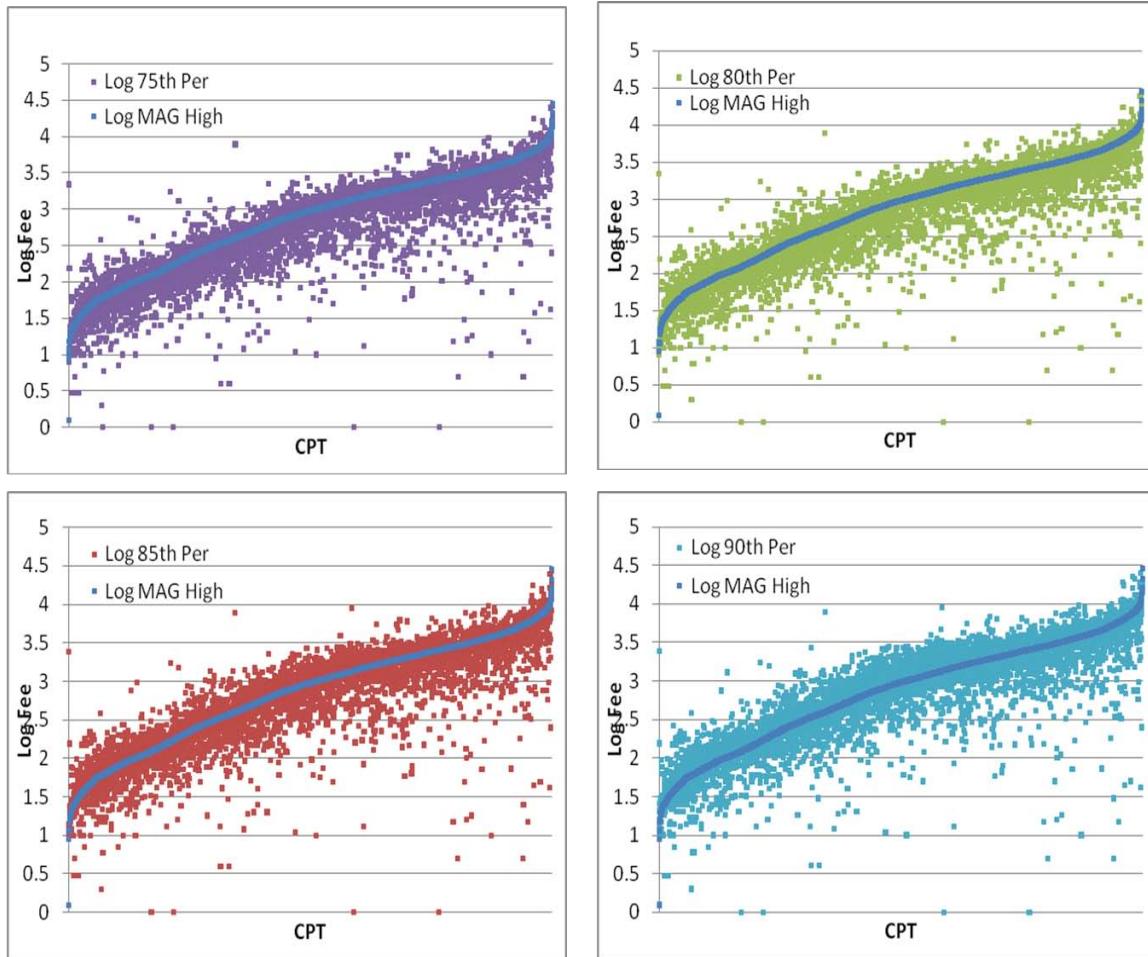


Figure C2: Comparison of MAG High Fee Value to Percentile Values from a MAG Independent Data Contributor, 2006



APPENDIX D: HIGH-LOW SCREEN TECHNICAL APPENDIX

Introduction

The purpose of this technical appendix is to describe a simulation performed which tests whether or not the Ingenix high-low screen systematically biases upper percentile values downward. Results of the simulation support the conclusion that the high-low screen sometimes decreases, increases, or leaves unchanged the upper percentile values of the original distribution.

Relationship between high-low screen and Foreman screen

In his analysis, Dr. Foreman does not actually use the high-low screen used by Ingenix.¹ Instead, he uses a variation of a scrubbing rule based on the classic Tukey method for identifying outliers.² Therefore, some discussion of how the formula for the high-low screen can be related to the Foreman and Tukey screens is necessary.

The traditional Tukey screen is:

Screen If Charge Is> (75th+(1.5*IQR))
Screen If Charge Is< (25th-(1.5*IQR))
Where IQR is the interquartile range, 75th is the 75th percentile value, and 25th is the 25th percentile value for the distribution.³

The Tukey screen that Dr. Foreman uses (“Foreman screen”) is:

Screen If Charge Is> (80th+(1.5*IQR))
Screen If Charge Is< (50th-(1.5*IQR))
Where 80th is the 80th percentile value, and 50th is the 50th percentile value for the distribution.⁴

The high-low screen used by Ingenix that apparently is understood by Plaintiffs’ experts is:

Screen if charge is > RV x per 80 x hifct
Screen if charge is < RV x per 50 x lowfct⁵
Where RV is the relative value for the procedure and the definition of “per 80” and “per50” are given in the paragraph below.

As Dr. Siskin explains:

Translated, the high formula (i.e., (i) above) means that Ingenix eliminates a

¹ Dr. Foreman acknowledges in his deposition that he did not analyze the actual Ingenix high-low screen in his report (*See* Foreman Merits Deposition Volume II at pp. 105:15-21, 108:13-16).

² *See* Foreman Report at ¶ 178.

³ *See* Tukey, J.W. 1977. *Exploratory Data Analysis*. Philippines: Addison-Wesley Publishing Company, Inc at p. 44.

⁴ Dr. Foreman explains: “We developed values for the 25th, 50th, 75th, and 80th percentiles of billed charges, the inter quartile range (IQR=75th-25th), the screen factor (1.5*IQR), the high screen value (80th+(1.5*IQR)) and the low screen value (50th-(1.5*IQR)).” *See* Foreman Report at ¶ 178.

⁵ *See* Plaintiffs’ Expert Report dated April 6, 2010 of Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the “Siskin Class Cert Report”) at p. 21.

contributed charge if it exceeds the product of the relative value for that CPT code multiplied by the 80th percentile for the combined data in the CPT code range (the “*per 80*”) multiplied by an arbitrary high factor number (hifct) determined by Ingenix.⁶

The values of the high and low factors (“hifct” or “fee high” and “lowfct” or “fee low”) that are used in the Common Scrubber formula are arbitrary.

Very similar high and low factor values have been in use since 1992.

Ingenix uses 1.95 as the high factor for all medical procedures; 1.8 as the high factor for all radiology procedures; 1.88 as the high factor for all laboratory procedures; and 1.9 as the high factor for all surgical procedures.⁷

There are differences between Dr. Foreman’s screen and that used by Ingenix. The Foreman screen does not include the relative value, the “per 80” and “per 50” factors, or the high and low factors of the Ingenix screen as described by Dr. Siskin. In contrast, the high-low screen does not depend directly on the 80th or 50th percentile value or the IQR of the distribution for a subject CPT/geozip combination of contributor billed charges. However, a mathematical representation of the high-low screen enables one to compare the results from the Ingenix high-low screen to the results of the Tukey and Foreman screens.

Mathematical representation of the high-low screen

Let 80_i^{th} equal the 80th percentile of a distribution of contributor billed charges for a specific CPT/geozip (“the original CPT/geozip”).

Define a transformation of this CPT/geozip’s data into indexed values as:

$$\text{Indexed Value}_i = \left(\frac{\text{Billed Charge}_i}{RV_j} \right)$$

where:

i = each element of the original CPT/geozip data, i = 1, ..., I, and

RV_j = the relative value of CPT j.

A specific set of CPTs by geozip are used to define the combined data in a CPT code range. This range pools the indexed values of the set of CPT_j, j = 1...J.

Let *per80* = the 80th percentile for the combined distribution for CPTs 1,...,J in a specific geozip (call this the 80th percentile conversion factor) and *per50* = the 50th percentile conversion factor, similarly defined, for the combined distribution.

⁶ See Siskin Class Certification Report at p. 22 (emphasis added).

⁷ See Siskin Class Certification Report at note 10.

Define β_{80} as the ratio of *per80* to the 80th percentile of the original distribution of billed charges for the CPT/geozip divided by the relative value for its CPT (and β_{50} similarly):

$$\beta_{80} = \left[\frac{per80}{\frac{80_i^{th}}{RV_j}} \right] = \frac{per80 * RV_j}{80_i^{th}}$$

$$\beta_{50} = \left[\frac{per50}{\frac{50_i^{th}}{RV_j}} \right] = \frac{per50 * RV_j}{50_i^{th}}$$

Rearranging:

$$per80 = \beta_{80} \left[\frac{80_i^{th}}{RV_j} \right]$$

$$per50 = \beta_{50} \left[\frac{50_i^{th}}{RV_j} \right]$$

Recall the approximate formula for the high-low screen:⁸

$$High\ Screen = RV_j * per80 * 2$$

$$Low\ Screen = RV_j * per50 * 0.3$$

Substituting for *per50* and *per80*:

$$High\ Screen = RV_j * \beta_{80} \left[\frac{80_i^{th}}{RV_j} \right] * 2$$

$$Low\ Screen = RV_j * \beta_{50} \left[\frac{50_i^{th}}{RV_j} \right] * 0.3$$

or:

$$High\ Screen = 2 * \beta_{80} [80_i^{th}]$$

$$Low\ Screen = 0.3 * \beta_{50} [50_i^{th}]$$

As a simplification, assume $\beta_{50} = \beta_{80} = \beta$.

⁸ The approximate values for hifct and lowfct are based on the Deposition Transcript of Carla Gee (Apr. 6, 2005), Exhibit Gee 10.

Therefore, the high-low screen can be represented by the following:

$$\text{High Screen} = 2 * \beta[80_i^{th}]$$

$$\text{Low Screen} = 0.3 * \beta[50_i^{th}]$$

This representation of the high-low screen can be compared to the Tukey and Foreman screens because now they are all functions of the 50th and 80th percentile values of the original distributions of billed charges by CPT/geozip.

Simulation of the high-low, Tukey, and Foreman screens – one period results

Given the comparative basis above, a simulation can be performed to examine the effects on the 80th percentile fee value of a classic Tukey screen (“Tukey”), Dr. Foreman’s derivation of the Tukey screen as an approximation for the high-low screen (“Foreman”), and Ingnenix’s actual high-low screen (“high-low”). The simulation examines the effects of the various screens described above on right skewed distributions, varying assumptions about the underlying levels of billed charges and the variation in billed charge values to address the robustness of the results.

The simulation produces data sets of 100,000 records each, lognormally distributed with various levels of means and standard deviations and variation in the values of Beta for different CPT/geozip distributions. The lognormal distribution was selected because it is a standard right skew distribution of non-negative values. Preliminary analysis indicated that the percentage differences between the screened and the unscreened data are similar across different mean levels but affected by the assumed standard deviation. Therefore, results are provided averaged across different “mean” levels and categorized by the standard deviation as indexed by the coefficient of variation (“CV”), a standard measure of variation in statistics.

Figures D-1 and D-2 show results for two different assumptions about Beta and seven assumptions about the CV. The vertical axis measures the percent difference between the 80th percentile values of the unscreened and screened data. The green results pertain to the high-low screen, the red results pertain to the Foreman screen, and the grey hatched results pertain to the traditional Tukey screen. The figures show that for $\beta = 0.5$ and $\beta = 1$, all screening methods decrease the 80th percentile values and this effect worsens with increasing variance in the distribution.

Figure D-1: Outlier Screen Simulation, $\beta = 0.5$

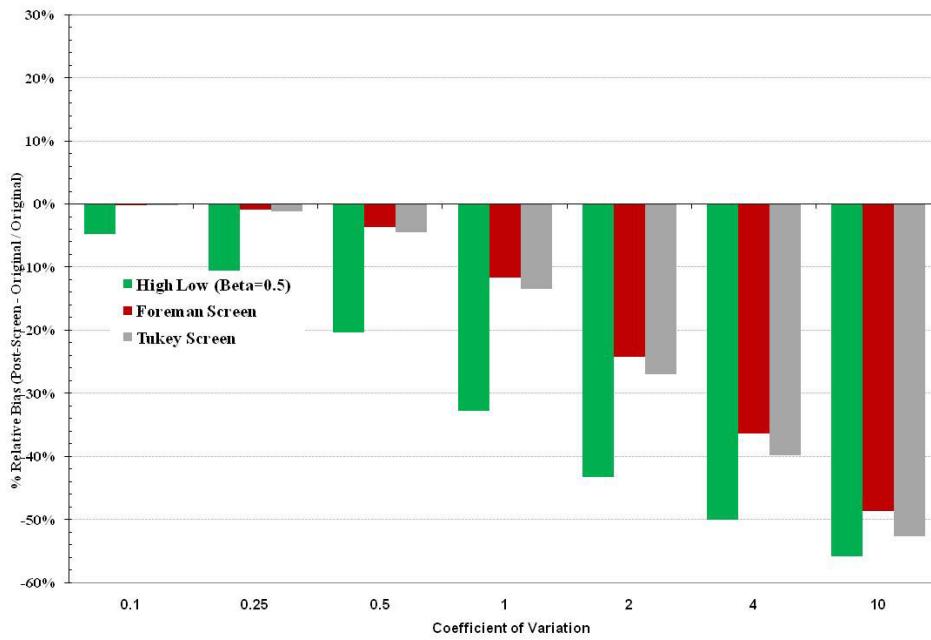
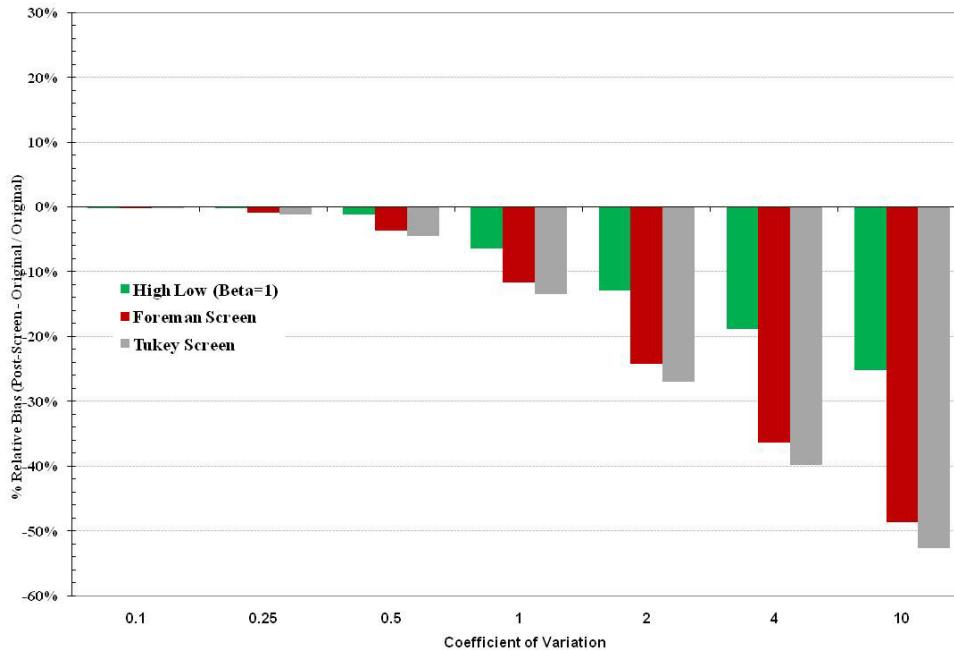


Figure D-2: Outlier Screen Simulation, $\beta = 1.0$

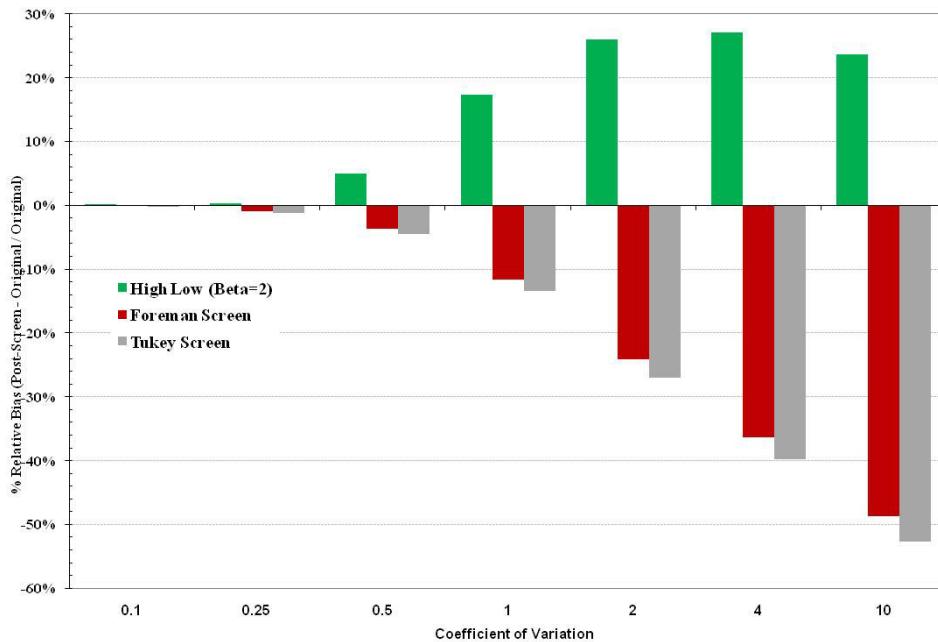


For $\beta = 0.5$, both the Foreman screen and the Tukey screen result in less decline in the value of the 80th percentile than the high-low screen. For, $\beta = 1$, the high-low screen results in less decline than the Foreman and Tukey screens. The reason for this switch in positions is the amount of high and low claims that are removed by the screen. With low values of Beta, the

high-low screen removes more high-value than low-value claims. At $\beta = 1$, this is less so, and importantly, the Foreman and Tukey screens are removing almost no low values from the billed charge distribution. This is because with higher variation, the width of the inter-quartile range (“IQR”) increases such that the low screen cut-off point, a multiple of the IQR, often falls below the lowest values in the right-skew distribution. As such, few or no low values are removed.

Figure D-3 shows the results when $\beta = 2$. The high-low screen, because it continues to remove low-value claims and will remove a greater number of them for higher values of β , now results in an *increase* in the 80th percentile values for most of the assumptions about variation. The Foreman and the Tukey screens continue to result in a decline because they are not affected by the relationship to the “per 80” or “per 50”. These screens depend only on the values and the IQR—reflecting variation in the values.

Figure D-3: Outlier Screen Simulation, $\beta = 2.0$



Repeated simulations indicate that the “switching” point from a negative to a positive bias occurs at approximately $\beta = 1.4$ for the high-low screen.⁹

$$\text{If } \beta \geq 1.4, \text{ then } 80_{\text{screened}}^{\text{th}} \geq 80_i^{\text{th}}.$$

In other words, in the simulation if $\beta \geq 1.4$, then the high-low screen will often lead to a screened 80th percentile value greater than the 80th percentile computed from the original billed charge value.

⁹ The value of the switching point varies a small amount depending upon the variance assumed.

Using the simulation, it was also investigated whether a switch in the bias from negative to positive could be produced with the Foreman screen. Table D-1 shows that for various assumptions about the mean levels and variation, the Foreman screen almost always reduces the unscreened 80th percentile value and never increases the value.

Table D-1: Simulated Percentile Values, No Screen v. Foreman Screen

CV (Standard Deviation/Mean)											
		0.1		0.5		1		2		4	
Mean	No Screen	Foreman Screen									
\$50	\$54.10	\$54.10	\$66.60	\$64.20	\$71.20	\$63.20	\$65	\$49.40	\$50	\$32	
\$100	\$108.20	\$108.10	\$133.10	\$128.30	\$142.50	\$125.40	\$13,012	\$99.70	\$100	\$63.50	
\$500	\$541.10	\$540.70	\$665.50	\$643.20	\$712.50	\$632.10	\$650.40	\$494.50	\$500	\$317.20	
\$1,000	\$1,082.20	\$1,081.60	\$1,331.10	\$1,283.10	\$1,424.90	\$1,256.60	\$1,300.80	\$985.30	\$1,000	\$636.60	
\$5,000	\$5,410.90	\$5,408.10	\$6,655.40	\$6,412.10	\$7,124.60	\$6,314.10	\$6,504.10	\$4,940.50	\$5,000.10	\$3,180.90	
\$10,000	\$10,821.80	\$10,810.20	\$13,310.80	\$12,796.90	\$14,249.30	\$12,550.90	\$13,008.20	\$9,897.60	\$10,000.20	\$6,425	

Simulation of the high-low, Tukey, and Foreman screens – multi-period results

In his report, Dr. Foreman also analyzes the effect of his screen on CIGNA data over time. As a corollary, the simulation model was used to investigate whether Dr. Foreman's serial results hold for the high-low screen, properly defined. To address the time series aspects of the comparison, the model was modified to use lagged values of the 50th and 80th percentile values to determine the screens—one of the alleged flaws in the Ingenix scrubbing protocol. Additionally, a three percent escalation factor was added to the values of the simulated annual data to reflect inflation that occurs naturally in actual billed charges.

Figure D-4 shows the results for $\beta = 1$ and $CV = 1$ with an assumed lognormal distribution with mean=\$100¹⁰. Beginning with the 80th percentile at approximately \$150, the simulation shows that both the Foreman and the high-low screens increasingly diverge from the No screen case over the nine periods.

¹⁰ Other mean values show a similar pattern.

Figure D-4: Outlier Screen Over Time, 3% Inflation, $\beta = 1$ (CV=1.0)

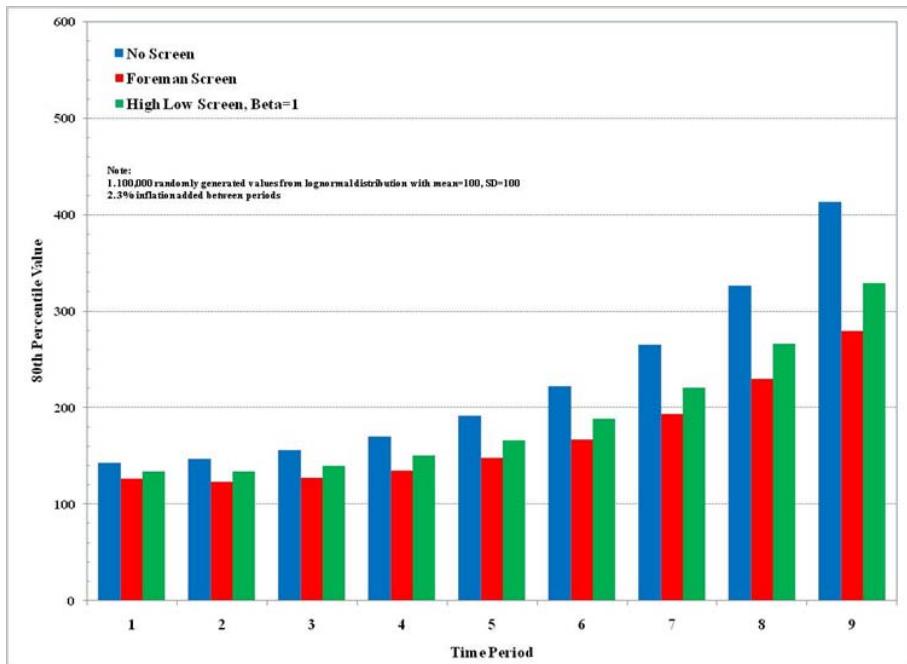
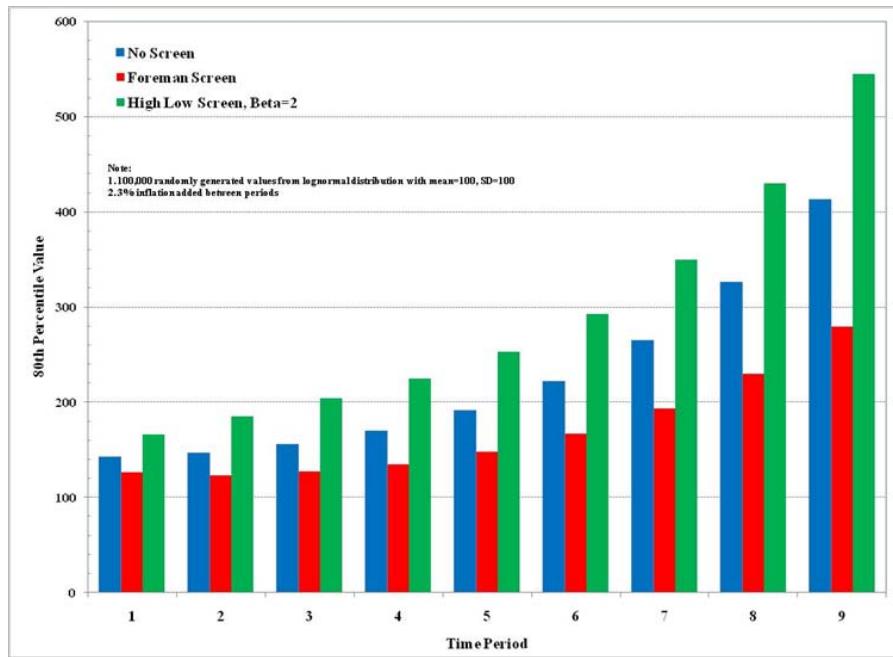


Figure D-5 shows the results when $\beta = 2$ is assumed. Despite using lagged data for determining the screens and the inclusion of a three percent annual escalation factor, the post-screen value of the 80th percentile is *larger* using the high-low screen method than for the No screen case. The Foreman screen method continues to produce a reduction in the 80th percentile value.

Figure D-5: Outlier Screen Over Time, 3% Inflation $\beta = 2.0$, (CV=1.0)





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ATTACHMENT 1: CANTOR CV

Robin A. Cantor, Ph.D. Principal

Professional Profile

Dr. Robin Ann Cantor is a Principal in Exponent's Alexandria, VA office. She specializes in applied economics, environmental and energy economics, statistics, risk management, and insurance claims analysis. Prior to joining Exponent, she led the Liability Estimation practice at Navigant Consulting and assisted companies and financial institutions with analysis to better understand asbestos and other product liability exposures. Other positions she has held include: Principal and Managing Director of the Environmental and Insurance Claims Practice at LECG, LLC, Program Director for Decision, Risk, and Management Sciences, a research program of the National Science Foundation, and senior research appointments at Oak Ridge National Laboratory. Dr. Cantor has a faculty appointment in the Graduate Part-time Program in Engineering of the Johns Hopkins University. She was the President of the Society for Risk Analysis in 2002, and from 2001-2003, she served as an appointed member of the Research Strategies Advisory Committee of the US Environmental Protection Agency's Science Advisory Board. She is a member of the Executive Committee for the Women's Council on Energy and the Environment. Dr. Cantor's testimonial experience includes analysis of economic damages, product liability estimation in bankruptcy matters and insurance disputes, statistical analysis of asbestos settlements, analysis of premises and product claims, cost contribution allocation in Superfund disputes, analysis of derailment risks, reliability of statistical models and estimation methods, and economic analysis of class certification issues. She has prepared expert reports that address economic issues in antitrust, commercial practices and contracts, intellectual property, employment discrimination, false advertising, regulation, and other areas of product and market analysis. Dr. Cantor has submitted analysis, testimony and affidavits in federal arbitration, regulatory and Congressional proceedings, and state and federal courts. Dr. Cantor's publications include refereed journal articles, book chapters, expert reports, reports for federal sponsors, and a book on economic exchange under alternative institutional and resource conditions.

Academic Credentials and Professional Honors

Ph.D., Economics, Duke University, 1985
B.S., Mathematics, Indiana University of Pennsylvania, 1978

Fellow, Society for Risk Analysis, 2002
President, Society for Risk Analysis, 2002
YWCA Tribute to Women Award for Business and Industry, 1990

Society for Risk Analysis Presidential Recognition Award, 2008; Society for Risk Analysis Outstanding Service Award, 1999; NSF Director's Award for Superior Accomplishment, 1996; NSF Special Act Award, 1995; NSF Director's Award for Program Officer Excellence, 1994;

Oak Ridge National Laboratory Significant R&D Accomplishment Award, 1993; Martin Marietta Special Achievement Award, 1990; Martin Marietta Special Achievement Award, 1989; Martin Marietta Energy Systems Significant Event Award, 1988; C.B. Hoover Scholar, 1980–1981; Mellon Fellowship, 1978–1981

Publications

Review Committee (Cantor RA – member). Review of the Department of Homeland Security's approach to risk analysis. National Research Council, The National Academies Press: Washington, D.C., 2010.

Cantor RA, Gunaseelan P, Vopelius J, Bandza A. Creating and financing the next-generation carbon offset project: An application to carbon capture and storage. In: Energy and Environmental Project Finance Law and Taxation: New Investment Techniques. Kramer AS, Fusaro PC (eds), Oxford University Press, 2010:15–38.

Cantor RA, Lyman M, Reiss R. Asbestos claims and litigation. *John Liner Rev* 2009; 23(2): 28–38.

Cantor RA, Hlavin A, Katofsky R, McDonald C. Current perspectives on trading environmental attributes. In: Energy and Environmental Trading: U.S. Law and Taxation. Kramer A, Fusaro P (eds), Cameron May, 2008; 183–235.

Cantor RA. Enterprise risk management perspectives on risk governance. In: Global Risk Governance: Concept and Practice using the IRGC Framework. Renn O, Walker K (eds), Springer Press, 2008.

Nieberding J, Cantor RA. Price dispersion and class certification in antitrust cases: An economic analysis. *J Legal Econ* 2007; 14(2):61–84.

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Nieberding J, Cantor RA. Price dispersion, the “Bogosian Short Cut,” and class certification in antitrust cases. ABA Antitrust Law, Economics Committee Newsletter 2004; 4(1):5–9. Also reprinted in Texas Business Litigation 2005; 23–25.

Zimmerman R, Cantor RA. State of the art and new directions in risk assessment and risk management: Fundamental issues of measurement and management. In: Risk Analysis and Society: An Interdisciplinary Characterization of the Field. McDaniels TL, Small MJ (eds), Cambridge University Press, 2004.

Cantor RA. Introduction to the 2001 best paper special issue. Risk Anal 2003; 23(6):1209–1210.

Adams GD, Cantor RA. Risk, stigma, and property values: What are people afraid of? pp. 175–186. In: Risk, Media and Stigma. Flynn J, Kunreuther H, Slovic P (eds), pp. 175–186, Earthscan Publications, Ltd., 2001.

Cantor RA, Rayner S, Henry S. Markets, distribution & exchange after societal cataclysm, Books for Business, December 2000.

Cantor RA. Discussion paper on net environmental benefits assessment for restoration projects after oil spills, or some reflections on the decision process. pp. 145–152. In: Restoration of Lost Human Uses of the Environment. Cecil G (ed), SETAC Press, 1999.

Cantor RA, Yohe G (eds). Economic analysis. pp. 1–93. In: Human Choice and Climate Change: An International Assessment, Volume 3: Tools for Policy Analysis. Rayner S, Malone EL (eds), Battelle Press, 1998.

Cantor RA (contributor), Jaeger CC, Renn O, Rosa EA, Webler T, McDonell G, Sergen G (eds.) Decision analysis. pp. 141–2216. In: Human Choice and Climate Change: An International Social Science Assessment State of the Art Report, Volume 3. Rayner S, Malone EL (eds), Battelle Press, 1998.

Cantor RA. Rethinking risk management in the federal government. Ann Am Acad Political Social Sci 1996; 545:135–143.

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Cantor RA. Applying construction lessons to decommissioning estimates. Energy J 1991; 12:105–117.

Cantor RA, Rizy C. Biomass energy: Exploring the risks of commercialization in the United States of America. Bioresource Technol 1991; 35(1):1–13.

Cantor RA, Krupnick A, Rizy C. Beyond the market: Recent regulatory responses to the externalities of energy production. pp. 51–61. Proceedings, 1991 Conference of the National Association of Environmental Professionals, 1991.

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Cantor RA, Jones D, Lieby P, Rayner S. Policies to encourage private sector responses to potential climate change. In: Energy Markets in the 1990s and Beyond. Finizza A, Weyant JP (eds), IAEE, Washington, DC, 1989.

Cantor RA, Hewlett J. The economics of nuclear power: Some new evidence on learning, economies of scale, and cost estimation. Resources Energy 1988; 10:315–335.

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Cantor RA, Rayner S, Braid RB. The role of liability preferences in societal technology choices: Results of a pilot study. In: Risk Assessment and Management. Lave L (ed), Plenum Press, New York, 1987.

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Cantor RA, Rayner S. The fairness hypothesis and managing the risks of societal technology choices. ASME, paper 86-WA/TS-5, December 1986.

Cantor RA. Regulatory trends and practices related to nuclear reactor decommissioning. In: The Energy Industries in Transition 1985–2000. Weyant JP, Sheffield DB (eds), IAEE, Washington, DC, 1984.

Other Publications

Cantor RA, Patrick B. Commercialization of nanotechnology: Enterprise risk management issues. Background Paper presented to the ABA Section of Environment, Energy, and Resources Nanotechnology Panel, 36th Annual Conference on Environmental Law, Keystone, CO, March 8–11, 2007.

Cantor RA, Zimmerman R. First World Congress on Risk “Risk and Governance” conference highlights. Risk Newsletter 2003; 23(4):1–10.

Cantor RA. Risk analysis in an interconnected world. RISK Newsletter 2001; 21(3):1–3.

Cantor RA, Zimmerman R. Risk and governance: An international symposium. RISK Newsletter 2001; 21(1):20–21.

Cantor RA. Book review of *Public Reactions to Nuclear Waste* by Riley E. Dunlap, Michael E. Kraft, and Eugene A. Rosa. Science 1994; 266:145.

Cantor RA. News from Washington. Human Dimensions Quarterly 1994; 1(2):20–21.

Cantor RA. Book review of *The Risk Professionals* by Thomas M. Dietz and Robert W. Rycroft. Environmental Professional 1989; 11(4):458–459.

Cantor RA. Decommissioning: The Next chapter in the nuclear saga. FORUM 1988; 3(3):105–106.

Technical Manuscripts

Menzie C, Cantor R, Boehm P, Bailey JR. An approach to business vulnerability and risk assessments related to climate change. SPE Paper Number SPE-127083-PP, November, 2009.

Analysis of the Estimated Production Cost Savings From Replacing the Dollar Note with the Dollar Coin. Final report of analysis submitted to Congressional Record, June 12, 2000 (with Jessica B. Horewitz and Robert N. Yerman).

Rebuttal Verified Statement with Gordon C. Rausser for CSX Corporation and CSX Transportation, Inc., Norfolk Southern Corp., and Norfolk Southern Railway Co., Control and Operating Leases/Agreements, Conrail Inc. and Consolidated Rail Corp., Railroad Control Application, Applicants’ Rebuttal Vol. 2B of 3, December, 1997.

Community Preferences and Superfund Responsibilities. Prepared for the USEPA under Interagency Agreement 1824-B067-A1 with Oak Ridge National Laboratory, August 1993.
Robin A. Cantor, Ph.D.

The U.S.-EC Fuel Cycle Study: Background Document to the Approach and Issues. Oak Ridge National Laboratory, ORNL/TM-2500, November, 1992 (with L. W. Barnhouse, D. Burtraw (Resources for the Future), G. F. Cada, C. E. Easterly, A. M. Freeman (Bowdoin College), W. Harrington (Resources for the Future), T.D. Jones, R. L. Kroodsma, A. J. Krupnick (Resources for the Future), R. Lee, H. Smith (DOE), A. Schaffhauser, and R. S. Turner).

What are the Problems of Equity and Legitimacy Facing a Management Strategy for the Global Commons? Managing the Global Commons: Decision Making and Conflict Resolution in Response to Climate Change, Oak Ridge National Laboratory, ORNL/TM-11619, July, 1990 (with Roger Kasperson in Steve Rayner, Wolfgang Naegeli, and Patricia Lund).

Markets, Distribution, and Exchange after Societal Cataclysm, Oak Ridge National Laboratory, ORNL-6384, November 1989 (with S. Rayner and S. Henry).

Information. Chapter 5 of A Compendium of Options for Government Policy to Encourage Private Sector Responses to Potential Climate Change, DOE/EH-0102, Report to Congress, October, 1989 (with G. G. Stevenson and P. J. Sullivan).

Agriculture and Forestry. Chapter 10 of A Compendium of Options for Government Policy to Encourage Private Sector Responses to Potential Climate Change, DOE/EH-0102, Report to Congress, October, 1989 (with W. Naegeli and A. F. Turhollow, Jr.).

Evaluation of Implementation, Enforcement and Compliance Issues of the Bonneville Model Conservation Standards Program, Vol. I and II, ORNL/CON-263, July 1989 (with Steve Cohn).

Gas Furnace Purchases: A Study of Consumer Decision Making and Conservation Investments. ORNL/TM-10727, October 1988 (with David Trumble).

An Analysis of Nuclear Power Plant Construction Costs. DOE/EIA-0485, 1986 (with J. G. Hewlett and C. G. Rizy).

Nuclear Reactor Decommissioning: A Review of the Regulatory Environments. ORNL/TM-9638, 1986.

Nuclear Power Options Viability Study, Vol. I, Executive Summary, ORNL/TM-9780/1, 1986 (with D. B. Trauger et al.).

Nuclear Power Options Viability Study, Vol III, Nuclear Discipline Topics. ORNL/TM-9780/3, 1986 (with D. B. Trauger et al.).

Clinch River Breeder Reactor: An Assessment of Need for Power and Regulatory Issues, ORNL/TM-8892, September 1983 (with D. M. Hamblin et al.).

Selected Presentations

Cantor RA. Evaluating vulnerabilities and identifying emerging risks. Invited presentation, The Conference Board EHS Legal Counsel Meeting, Houston TX, January 15–16, 2009.

Cantor RA. Using exposure science to ascertain asbestos liabilities. Invited CLE presentation, Business Valuation Resources, LLC Teleconference, November 18, 2008.

Cantor RA. Weather and temperature: Emerging health issues for US companies. REBEX 2008, Wheeling IL, October 23–24, 2008.

Cantor RA. Asbestos risk transfers: Unlocking value by walling off asbestos liabilities. Invited CLE session at Willkie Farr & Gallagher, New York, NY, June 4, 2008.

Cantor RA. The future of asbestos—New techniques for unlocking value by selling liabilities to investors. Mealey's™ Teleconference, March 25, 2008.

Cantor RA. Update on other U.S. long-tailed product liabilities. Invited presentation, 4th International Asbestos Claims & Liabilities Conference: The Practical Guide to Litigating, Settling and Managing Asbestos Claims, London, January 30–31, 2008.

Cantor RA. Tax or cap: What are the real differences for carbon policy in the US? Invited session and presentation, McDermott Will & Emery 10th Annual Energy Conference, Washington DC, October 9–10, 2007.

Cantor RA. Managing nanotechnology's life cycle risks responsibly. Invited ALI-ABA teleconference, June 27, 2007.

Cantor RA. Carbon emissions—Planning for the change. Invited teleconference, Environmental Law Network, June 15, 2007.

Cantor RA. Liability estimation and the historical future. Invited presentation, Mealey's™ Asbestos Bankruptcy Conference, Chicago, IL, June 7–8, 2007.

Cantor RA. Renewables and the value proposition for carbon credits. Invited presentation, McDermott Will & Emery 9th Annual Energy Conference, Washington DC, October 19–20, 2006.

Cantor RA. The ABCs of the value proposition for carbon credits. Invited presentation, the Environmental Trading Congress, New York, NY, July 24–25, 2006.

Cantor RA, Lyman M. Liability estimation in U.S. bankruptcy cases. London Underwriting Centre, London, UK, January 10, 2006.

Cantor RA, Lyman M. The status of the FAIR Act. London Underwriting Centre, London, UK, January 10, 2006.

Cantor RA. Economic appraisal of ecological assets. Invited presentation, U.S. Environmental Protection Agency Science Advisory Board “Science and the Human Side of Environmental Protection” Series, Washington, DC, July 6, 2002.

Cantor RA. Scientists and Homeland Security—The relevance of risk analysis. Invited presentation, Council of Scientific Society Presidents, Washington, DC, May 2002.

Cantor RA. NRD rules and economics. Invited presentation, Environmental and Admiralty Law Committees of the Association of the Bar of the City of New York, December 7, 2000.

Cantor RA. Revealed preferences and environmental risks: Lessons learned from two policy debates. Annual Meetings of the Society For Risk Analysis, Phoenix, AZ, December 8, 1998.

Cantor RA. Valuing environmental impacts: Lessons learned from the natural resource damage debate. Invited Paper, Society of Environmental Toxicology and Chemistry, 19th Annual Meeting, November 19, 1998.

Cantor RA. How will climate change affect economics and politics? Invited panel speaker, Policy and Politics of Climate Change, ABA Section of Natural Resources, Energy, and Environmental Law Fall Meeting, October 8, 1998.

Cantor RA. Natural resource damage rules: A search for the path of least resistance in value disputes? George Washington University Seminar Series on Environmental Values and Strategies, September 1997.

Cantor RA. Rethinking the science of risk management: Changing paradigms of the process and function. Operations and Information Management Department Workshop, Wharton School of the University of Pennsylvania, November 1995.

Cantor RA, Arkes H. Interdisciplinary perspectives on experimental methods. 1995 Meetings of the American Economic Association, January 1995.

Cantor RA. Risk management: Four different views. Invited presentation, The Conservation of Great Plains Ecosystems Symposium, April 1993.

Cantor RA. Human dimensions of global change: A white paper on the USGCRP research programs. National Academy of Sciences Board on Global Change, November 1993.

Cantor RA, Rayner S. Changing perceptions of vulnerability. Invited paper, NCAR/UCAR Summer Institute on Industrial Ecology and Global Change, July 17–31, 1992.

Cantor RA. Should economic considerations limit the conservatism of risk assessment? Invited paper, Workshop of the International Society of Regulatory Toxicology and Pharmacology on Risk Assessment and OMB’s Report on its Application in Regulatory Agencies, Washington, DC, June 11, 1991.

Cantor RA. Beyond the market: Recent regulatory responses to the externalities of energy production. Annual Meetings of the National Association of Environmental Professionals, Baltimore, MD, April 30, 1991.

Cantor RA. Understanding community preferences at Superfund sites. National Meeting of EPA Community Relations Coordinators, Chicago, IL, April 4–6, 1990.

Cantor RA. Methodological myths and modeling markets: A common framework for analyzing exchange. Second Annual International Conference on Socio-Economics, Washington, DC, March 1990.

Cantor RA, Schoepfle GM, Szarleta EJ. Sources and consequences of hypothetical bias in economic analyses of risk behavior. 1989 Meetings of Society for Risk Analysis, October 1989.

Cantor RA, Jones D, Lieby P, Rayner S. Policies to encourage private sector responses to potential climate change. 1989 Meetings of International Association of Energy Economists, October 1989.

Cantor RA, Szarleta EJ. The experimental approach in public policy analysis: precepts and possibilities. Public Choice Society and Economic Science Association Annual Meetings, Orlando, FL, March 17–19, 1989.

Cantor RA, Rayner S. Global disaster management: Developing principles for research. 1988 Meetings of the Association for Public Policy Analysis and Management, October 1988.

Cantor RA. Implementation and enforcement issues from early adopter experience. Regional Evaluation Network, Northwest Power Planning Council, Portland, OR, June 1988.

Cantor RA. Using information from toxic-tort litigation to value the health and safety consequences of regulatory decisions. Public Policy Workshop, the Department of Economics and Waste Management Research and Education Institute, University of Tennessee, Knoxville, TN, February 1988.

Cantor RA, Bishop R, Jr. Valuing safety and health effects in regulatory decisions: A revealed-preference approach. 1987 Annual Meeting of the Society for Risk Analysis, November 3, 1987.

Cantor RA. Government intervention and technology prices: The CANDU example. Invited paper, WATTEC Conference, Knoxville, TN, February 19, 1987.

Cantor RA. Fairness hypothesis and managing the risks of societal technology choices. 1986 Winter Annual Meeting of the American Society of Mechanical Engineers, Anaheim, CA, December 10–12, 1986.

Cantor RA. A retrospective analysis of technological risk: The case of nuclear power. Invited paper, Center of Resource and Environmental Policy Workshop Series, Vanderbilt University, Nashville, TN, December 4, 1986.

Cantor RA, Petrich C, Mercier J-R. Evaluation of a large-scale charcoal project in Madagascar: Attacking the deforestation problem from the supply side. 1986 IAEE North American Conference, Cambridge, MA, November 19–21, 1986.

Cantor RA, Rayner S. Tools for the job: Choosing appropriate strategies for risk management. 1986 Annual Meeting of the Society for Risk Analysis, Boston, MA, November 9–12, 1986.

Cantor RA, Rayner S. Thinking the unthinkable: Preparing for global disaster. 1986 Annual Meeting of the Society for Risk Analysis, Boston, MA, November 9–12, 1986.

Cantor RA, Rayner S, Braid B. The Role of liability preferences in societal technology choices: Results of a pilot study. 1985 Annual Meetings of Society for Risk Analysis, Washington, DC, October 8, 1985.

Conference Participation

Invited panelist for “An Integrated Risk Framework for Gigawatt-Scale Deployments of Renewable Energy: The Wind Energy Case Study,” 2009 Annual Meeting for the Society for Risk Analysis, Baltimore, MD, December 9, 2009.

Invited session organizer and panelist for “Global Warming and Greenhouse Gas Controls: What do they mean for you?” 2008 Annual Meeting of the National Association of Publicly Traded Partnerships, Washington DC, June 26, 2008.

Co-chair, “Second World Congress on Risk,” Guadalajara, Mexico, June 2008.

Invited panelist for “Climate Litigation: The Next Asbestos or the Next Y2K?” ABA Section of Litigation Annual Conference, Washington DC, April 17, 2008.

Invited panelist for “Business of Mitigation: Carbon Offsets and Trading,” Oxford University Capstone Conference, Oxford, UK, September 10, 2007.

Panelist for “Issues Concerning Implementation,” at the Public Forum on OMB’s Proposed Risk Assessment Bulletin: Implications for Practice Inside and Outside Government, sponsored by Society for Risk Analysis, Society of Environmental Toxicology and Chemistry in North America, Society of Toxicology, and International Society of Regulatory Toxicology and Pharmacology.

Session Chair, “Challenges Facing Industrial Countries,” with key-note speeches by Philippe Busquin, EU Commissioner for Research, and Dr. John Graham, Administrator of the US Office of Information and Regulatory Affairs, Inaugural Conference of the International Risk Governance Council, Geneva, Switzerland, June 29, 2004.

Co-Chair, "First World Congress on Risk," Brussels, Belgium, June 2003.

Chair of the Organizing Committee, 2001 Annual Meetings for the Society for Risk Analysis.

Member of the Organizing Committee, Risk and Governance Symposium, Society for Risk Analysis, June 2000.

Organizing Committee Member for the 1996, 1997, 1998, and 2002 Annual Meetings of the Society for Risk Analysis.

Panelist for Net Environmental Benefits Assessment for Restoration Projects after Oil Spills, Conference on Restoration for Lost Human Uses of the Environment, Washington, DC, May 1997.

Session Organizer and Chair for Cost Benefit Analysis and Risk Assessment at the 1996 Annual Meeting of the Society for Risk Analysis.

Panelist for Challenges in Risk Assessment and Risk Management sponsored by The Annenberg Public Policy Center of the University of Pennsylvania at the National Press Club, Washington, DC, May 16, 1996.

Panelist for Media and Risk in a Democracy: Who Decides What Hazards Are Acceptable? At the 1995 Annual convention of the Association for Education in Journalism and Mass Communication.

Session Organizer and Co-Chair for Experimental Methods: Insights from Economics and Psychology at the 1995 Meetings of the American Economic Association.

U.S. Organizer for the Third Japan-U.S. Workshop on Global Change Modeling and Assessment: Improving Methodologies and Strategies, Hawaii, October 1994.

Cluster Organizer for three sessions on Competitiveness at the Fall Meeting of the Operations Research Society of America/The Institute of Management Sciences, 1994.

Roundtable Panelist for Risk Communication Research: Defining Practitioner Needs at the 1994 Meetings of the Society for Risk Analysis.

Workshop Organizer for Organizational Transformation and Quality Systems, National Science Foundation, 1993.

Session Chair and Organizer for the NSF/Private Sector Research Initiative Projects at the 1992 Meetings of the Society for Risk Analysis.

Roundtable Panelist for the EPA Session on Risk Communication at the 1990 Meetings of the Society for Risk Analysis.

Session Chair and Organizer for the Computer Assisted Market Institutions Session at the Advanced Computing for the Social Sciences Conference, April 1990.

Discussant for the Issues in LDC Public Finance Session at the 1988 Meetings of the American Economic Association.

Session Chair and Organizer for Social Science Innovations in Risk-Analysis Methods, Special Session at the 1988 Meetings of the Society for Risk Analysis.

Prior Experience

Managing Director, Navigant, 2004–2008

Lecturer, Graduate Program, Johns Hopkins University, Engineering and Applied Science Programs for Professionals, Program in Environmental Engineering, Science and Management, 1996–present

Principal and Managing Director, LECG, 1999–2004

Senior Managing Economist, LECG, 1999

Managing Economist, LECG, 1996–1998

Member, U.S. Environmental Protection Agency, Science Advisory Board, Research Strategies Advisory Committee, 2001–2003

Program Director, Decision, Risk, and Management Science, National Science Foundation, 1992–1996

Coordinator, NSF Human Dimensions of Global Change, 1992–1996

Project Manager, Oak Ridge National Laboratory, 1990–1991

Technical Assistant to the Associate Director, Advanced Energy Systems, Oak Ridge National Laboratory, 1989–1990

Group Leader, Social Choice and Risk Analysis Group, Energy and Economic Analysis Section, Oak Ridge National Laboratory, June 1987–1989

Research Staff, Energy and Economic Analysis Section, Oak Ridge National Laboratory, Oak Ridge National Laboratory, October 1982–1987

Consultant, Indonesian Energy Project, Harvard Institute For International Development, July 1987

Visiting instructor, North Carolina Central University, Spring 1982

Advisory and Other Appointments

- National Research Council Committee to Review the Department of Homeland Security's Approach to Risk Analysis, November, 2008–present
- Executive Committee, Women's Council on Energy and the Environment, 2006–present
- Board Member, Women's Council on Energy and the Environment, 2004–2006
- Member, Advisory Group for the Joint Global Change Research Institute, a collaboration between Pacific Northwest National Laboratory and the University of Maryland, 2004–2008

- Member, Planning Committee for a study to evaluate the U.S. National Assessment of the Potential Consequences of Climate Variability and Change, coordinated through Carnegie Mellon University, 2004
- Neutral technical panelist working with Arbitrator Anthony Sinicropi on negotiation issues related to the pilots' compensation contract. Retained by US Airways and the Air Line Pilots Association (ALPA), 2001 and 2002
- Advisory Board Member, Johns Hopkins University Graduate Part-Time Program in Environmental Engineering and Science, 2000–2004
- Planning Committee Member, Carnegie Council on Ethics and International Affairs Long Term Study of Culture, Social Welfare, and Environmental Values in the U.S., China, India, and Japan, initiated January 1997
- Vice-Chair, U.S. Global Change Research Program working group on Assessment Tools and Policy Sciences, 1994–1996
- US Federal Reviewer for the Intergovernmental Panel on Climate Change working group III 1995 Report on Socioeconomics
- NSF Principal for the Committee on the Environment and Natural Resources' Subcommittee on Risk Assessment, 1993–1996. Also served as the liaison between the Subcommittee on Risk Assessment and the Subcommittee on Social and Economic Sciences
- Advisory panel member for Environmental Ethics and Risk Management, National Academy of Public Administration and George Washington University, 1993–1994
- Science Advisory Board member for Consortium for International Earth Science Information Network, 1993
- Review Panel member for Economics and the Value of Information, NOAA, 1993
- NSF technical representative to the FCCSET Ad Hoc Working Group on Risk Assessment and member of its Subcommittee on Risk Assessment, 1992–1993
- NSF representative to Working Party of the FCCSET Subcommittee for Global Change Research on Assessment, 1992–1993
- Affirmative Action Representative for the Energy Division, Oak Ridge National Laboratory 1984–1989, AA Rep for the Central Management Organization of ORNL, October 1989 to November 1990
- Board of Directors, Vice President (1987–1988), President (1988–1989), Matrix Organization, The Business Center for Women and Minorities, Knoxville, TN

Editorships and Editorial Review Boards

- Editorial Board, *Journal of Risk Analysis*, 1997–present
- Editorial Board, *Journal of Risk Research*, 1997–2005

Peer Reviewer

- The Energy Journal, Climate Change, Contemporary Economic Policy, Growth and Change, Ecological Applications, Risk Analysis, Duke University Press, Princeton University Press, J. of Environmental Economics and Management, Resources and Energy, The Environmental Professional, Journal of Risk Research, National Science Foundation, National Oceanic and Atmospheric Administration, FORUM, U.S. Environmental Protection Agency

Professional Affiliations

- American Economic Association
- Women's Council on Energy and the Environment
- Society for Risk Analysis
 - President, Society for Risk Analysis, 2002
 - President-Elect, Society for Risk Analysis, 2001
 - Councilor, Society for Risk Analysis, 1996–1999
- American Bar Association



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ATTACHMENT 2: CANTOR TESTIMONY

**Robin A. Cantor, Ph.D.
Principal**

In the Matter of the Rehabilitation of the Centaur Insurance Company
Office of Special Deputy Receiver and Sidley Austin LLP (Centaur Insurance)

- Deposition (April 11, 2006)

Class Plaintiffs v. American Heritage Life Insurance Company et al.
Polsinelli Shalton Welte Suelthaus PC and King & Spalding (Defendants)
Missouri State Court (03-CV-233109)

- Affidavit (October, 2006)

Class Plaintiffs v. American Express Company and American Express Travel Services Company, Inc.

Friedman Law Group LLP (Plaintiffs)
US District Court Southern District of New York (04 Civ. 05432 (GBD))

- Declaration (November, 2007)
- Deposition (November 27, 2007)
- Reply Declaration (March, 2008)

In the Matter of Dana Corporation, Debtors.

Jones Day (Debtor)
US Bankruptcy Court, Southern District of New York

- Trial Testimony (December 11, 2007)

In re Packaged Ice Antitrust Litigation

Spector, Roseman, Kodroff & Willis, P.C. (Class Plaintiffs)
US District Court Eastern District of Michigan

Case No. 2:08-md-01952 (PDB) MDL No. 1952

- Declaration (December, 2008)

The Howard Hughes Properties and Howard Hughes Corporation v. Kern River Gas Transmission Company

Bracewell & Giuliani LLP (Plaintiffs/Counterdefendants)

US District Court District of Nevada

Case No. 2:09-cv-00657-RLH-LRL

- Affidavit (October, 2009)
- Deposition (December, 2009)

TYR Sport Inc. v. Warnaco Swimwear Inc. dba Speedo USA

O'Neil LLP (Plaintiffs/Counterdefendants)

Case No. SACV 08-529-JVS(MLGx)

US District Court Central District of California

- Declaration (March 22, 2010)
- Declaration (April 5, 2010)
- Declaration (April 9, 2010)

In re Aetna UCR Litigation

Gibson, Dunn & Crutcher LLP (Defendants)

MDL No. 2020 Case No. 2:07-CV-3541

US District Court District of New Jersey

- Deposition (May 25, 2010)

ATTACHMENT 3: MATERIALS CONSIDERED

I. MATERIALS INCORPORATED BY REFERENCE

The materials cited in the footnotes to the Cantor Class Certification Report and the Updated Responsive Class Certification Report of Dr. Robin Cantor in the instant matter and/or listed in Attachments 3 and R2 thereto respectively are incorporated herein by reference.

II. LEGAL DOCUMENTS

A. Depositions

Deposition Transcript of Carla Gee (Apr. 6, 2005).
Deposition Transcript of Daniel Slottje (ROUGH DRAFT) (May, 5, 2010).
Deposition Transcript of Bernard Siskin, Ph.D. (May 13, 2010).
Deposition Transcript of Bernard Siskin, Ph.D. (ROUGH TRANSCRIPT) (May 14, 2010).
Deposition Transcript of Stephen Foreman (May 17-18, 2010).
Deposition Transcript of Dr. Andrew Joskow (ROUGH) (May 19, 2010).
Deposition Transcript of Darlery Frano (ROUGH TRNASCRIPT) (May 20, 2010).
Deposition Transcript of Dr. Gordon Rausser (ROUGH DRAFT) (May 21, 2010).
Deposition Transcript of Dr. Robin Cantor (ROUGH TRANSCRIPT) (May 25, 2010).
Deposition Transcript of Catherine Hanson (Jun. 21-22, 2010).
Deposition Transcript of Leonard A. Nelson, Esq. (Jun. 22, 2010).
Deposition Transcript of Lee Spangler (ROUGH TRANSCRIPT) (Jul. 2, 2010).
Deposition Transcript of Lee Spangler (Jul. 2, 2010).
Deposition Transcript of Matthew Katz (ROUGH) (Jul. 9, 2010).
Deposition Transcript of Matthew Katz (Jul. 9, 2010).
Deposition Transcript of Andrew Yarnell Beatty (Jul. 9, 2010).
Deposition Transcript of Donald Palmisano (Jul. 15, 2010).
Deposition Transcript of Stephen Keene (Jul. 21, 2010).
Deposition Transcript of Donald Moy (Jul. 21, 2010).
Deposition Transcript of Lawrence Downs (Jul. 22, 2010).
Deposition Transcript of Tim Layton (Jul. 27, 2010).
Deposition Transcript of Jeff Scott (Jul. 27, 2010).
Deposition Transcript of Barry Helfmann (Jul. 28, 2010).
Deposition Transcript of Jodi Black (Jul. 29, 2010).
Deposition Transcript of Michael King (Jul. 29, 2010).
Deposition Transcript of Stephen Foreman (ROUGH) (Nov. 1-2, 2010).

B. Expert Reports

Report in the Matter of Aetna UCR Litigation by Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 30, 2010).

Responsive Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed May 1, 2010).

Updated Responsive Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed May 1, 2010).

Responsive Report of Stephen Foreman, PhD, JD, MPA, In Re: Aetna UCR Litigation (MDL No, 2020 filed May 1, 2010).

Responsive Class Certification Expert Report of Monica G. Noether, Ph.D., Franco v. Connecticut General Life Insurance Co. (May 28, 2010).

Expert Report of Dr. Daniel J. Slottje on Class Certification Issues (REDACTED), Franco v. Connecticut General Life Insurance Co. (Jun. 30, 2010).

Expert Report of Dr. Daniel J. Slottje on Class Certification Issues, Franco v. Connecticut General Life Insurance Co. (Jun. 30, 2010).

Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010).

Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A. (CORRECTED), In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010).

Expert Witness Report of Gordon Rausser, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010).

Expert Report dated August 9, 2010 of Bernard R. Siskin, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010).

Affirmative Merits Expert Report of Dr. Daniel J. Slottje, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010).

C. Other

Order on Informal Application, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 14, 2010).

Declaration of Robert J. Axelrod, In Re: Aetna UCR Litigation (MDL No. 2020 filed May 29, 2010).

Memorandum of Law in Support of Plaintiffs' Motion for Class Certification (MDL No. 2020 filed May 29, 2010).

Declaration of James Laporta, In Re: Aetna UCR Litigation (MDL No. 2020 filed Jul. 1, 2010).

Memorandum of Law in Support of Aetna's Motion to Exclude Certain Purported Expert Testimony, In Re: Aetna UCR Litigation (MDL No. 2020 filed Jul. 2, 2010).

Aetna's Opposition to Plaintiffs' Motion for Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 filed Jul. 2, 2010).

Order on Informal Application, In Re: Aetna UCR Litigation (MDL No. 2020 filed Jul. 23, 2010).

Order on Informal Application, Michelle Cooper, et al. v. Aetna Health Inc., et al. and Darlery Franco, et al. v. Connecticut General Life, et al. (D.N.J. filed Jul. 23, 2010).

Certificate of Service, Notice of Motion, Motion, and Memorandum of Law, all in Support of Plaintiffs' Motion to Strike Declarations, along with a Proposed Order, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23 2010).

Certificate of Service, Plaintiff's Consolidated Memorandum in Opposition to Defendants' Motions to Exclude the Reports and Testimony of Dr. Bernard R. Siskin, Dr. Stephen Foreman, and Dr. Gordon Rausser, along with the Declaration of Robert J. Axelrod in support thereof, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23 2010).

Certificate of Service, Reply Memorandum in Further Support of Plaintiffs' Motion for Class Certification, Declaration of Robert J. Axelrod in support thereof, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23 2010).

Declaration of Robert J. Axelrod in Opposition to Defendants' Motions to Exclude the opinions Dr. Bernard R. Siskin, Dr. Stephen Forman, and Dr. Gordon Rausser, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23, 2010).

Declaration of Robert J. Axelrod in Support of Plaintiffs' Motion to Strike Declarations, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23, 2010).

Memorandum of Law in Support of Plaintiffs' Motion to Strike Declarations, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23, 2010).

Notice of Motion, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23, 2010).

Plaintiffs' Consolidated Memorandum in Opposition to Defendants' Motions to Exclude the Reports and Testimony of Dr. Bernard R. Siskin, Dr. Stephen Foreman, and Dr. Gordon Rausser, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23, 2010).

Proposed Order, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 23, 2010).

Reply Declaration of Robert J. Axelrod in Further Support of Plaintiffs' Motion for Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 24, 2010).

Reply Memorandum of Law in Further Support of Plaintiffs' Motion for Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 24, 2010).

Order on Informal Application, In Re: Aetna UCR Litigation (MDL No. 2020 filed Sep. 8, 2010).

Order on Informal Application, In Re: Aetna UCR Litigation (MDL No. 2020 filed Oct. 8, 2010).

III. BATES STAMPED DOCUMENTS

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INGENIXMDL000461979 – INGENIXMDL 000461994
INGENIXMDL000626485 – INGENIXMDL 000626488
INGENIXMDL000749854 – INGENIXMDL 000749857
INGENIXMDL000873202 – INGENIXMDL 000873207
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INGENIXMDL 000929773 – INGENIXMDL 000929775
INGENIXMDL 001125943 – INGENIXMDL 001125951
MAGMUT 000001 – MAGMUT 009003
MAGMUT 009003.0001

IV. DATASETS

A. MAG Mutual

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MAG Mutual, “Opticon.log,” Listing of the names and file locations of MAGMUT 000001 – MAGMUT 009003 and MAGMUT 009003.0001 (Jun. 9, 2010).

B. Ingenix Contributor Data

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Zip file “cg_0306.zip.”	Zip file “cg_0308.zip.”
Zip file “cg_0406.zip.”	Zip file “cg_0408.zip.”
Zip file “cg_0506.zip.”	Zip file “cg_0508.zip.”
Zip file “cg_0606.zip.”	Zip file “cg_0608.zip.”
Zip file “cg_0706.zip.”	Zip file “cg_0708.zip.”
Zip file “cg_0806.zip.”	Zip file “cg_0808.zip.”
Zip file “cg_0906.zip.”	Zip file “cg_0908.zip.”
Zip file “cg_1006.zip.”	Zip file “cg_1008.zip.”
Zip file “cg_1106.zip.”	Zip file “cg_1108.zip.”
Zip file “cg_1206.zip.”	Zip file “cg_1208.zip.”
GZip file “cg_34xx.txt.gz.”	GZip file “cg_39xx.txt.gz.”
GZip file “cg_36xx.txt.gz.”	GZip file “cg_40xx.txt.gz.”
GZip file “cg_37xx.txt.gz.”	GZip file “cg_uhg_pwc_36.unl.gz.”
GZip file “cg_38xx.txt.gz.”	GZip file “cg_uhg_pwc_37.unl.gz.”
GZip file “cg_uhg_pwc_38.unl.gz.”	Roshal Archive file “cg_uhg_pwc_35_2007.rar.”

TrueCrypt, “Procedure for Accessing TrueCrypt Drives,” Instructions for decrypting data encrypted using the TrueCrypt software (Dec. 9, 2009).

C. Medicare

Centers for Medicare & Medicaid Services. 2009. "Physician/Supplier Procedure Summary Master File,"
http://www.cms.gov/NonIdentifiableDataFiles/06_PhysicianSupplierProcedureSummaryMasterFile.asp (last visited Nov. 7, 2010).

D. Relative Values

Excel File "rlv2006.xlsx"
Excel File "rlv2007.xlsx"
Excel File "rlv2008.xlsx"

E. Zip-Code Data

Zip-codes.com, ZIP-Codes-Database-deluxe-business.csv, *available at www.zip-codes.com* (last visited Nov. 9, 2010).
Zip-codes.com, ZIP-Codes-Database-multi-county.csv, *available at www.zip-codes.com* (last visited Nov. 9, 2010).
Zip-codes.com, C170101.DBF, *available at www.zip-codes.com* (last visited Nov. 9, 2010).
Zip-codes.com, C18101.DBF, *available at www.zip-codes.com* (last visited Nov. 9, 2010).
Zip-codes.com, C550101.DBF, *available at www.zip-codes.com* (last visited Nov. 9, 2010).

V. PUBLICALLY AVAILABLE INFORMATION

A. Peer-Reviewed Articles

Benn, P.A., et al. 1999. "Cost-Effectiveness of Estimating Gestational Age by Ultrasonography in Down Syndrome Screening," *Obstetrics & Gynecology*, July 94(1): pp. 29-33.
Bree, R.L., et al. 2001. "Use of a Decision-Analytic Model to Support the Use of a New Oral US Contrast Agent in Patients with Abdominal Pain," *Academic Radiology*, March 8(3): pp. 234-242.
Busbee, B.G., et al. 2003. "Cost-Utility Analysis of Cataract Surgery in the Second Eye," *Ophthalmology*, December 110(12): pp. 2310-2317.
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Luebbers D., et al. 2003. "Systematic Development of Data Mining-Based Quality Tools," In Proceedings of the 29th Very Large Data Base Conference, Berlin, Germany.

Mirkin, D.P., et al. 2000. "Getting Paid in the Managed Care Workplace: The Basics of Physician Compensation," *Hospital Physician*, January: pp. 69-79.

Rentz, A.M., et al. 1998. "The Impact of Candidemia on Length of Hospital Stay, Outcome, and Overall Cost of Illness," *Clinical Infectious Diseases*, October 27: pp. 781-788.

Rodney, W.M., et al. 2002. "Impact of the Limited Generalist (No Hospital, No Procedures) Model on the Viability of Family Practice Training," *JABFP*, May-June 15(3): pp. 191-200.

Roland, P.Y., et al. 1995. "A Decision Analysis of Practice Patterns Used in Evaluating and Treating Abnormal Pap Smears," *Gynecologic Oncology*, February 59: pp. 75-80.

Sherman, E.J., et al. 2001. "The Collection of Indirect and Nonmedical Direct Costs (COIN) Form," *CANCER*, February 91(4): pp. 841-853.

B. Database Manuals and Materials

Healthcare Cost and Utilization Project, "HCUP Kids' Inpatient Database Design Report, 1997," Manual for data collection and editing (Jan. 28, 2002).

World Health Organization, "The World Health Organization Global Database on Child Growth and Malnutrition: Methodology and Applications, 2003," Manual for data collection and editing (Jan. 7, 2003).

Moeller JF, Stagnitti MN, Horan E., et al. Outpatient Prescription Drugs: Data Collection and Editing in the 1996 Medical Expenditure Panel Survey (HC-010A), Rockville (MD): Agency for Healthcare Research and Quality; 2001. MEPS Methodology Report 12, AHRQ Pub. No. 01-0002.

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Leslie Schafer, Ph.D., "Teleconference with Thomas McCurdy – EPA – re CHAD Data – 6.24.10," Internal memo documenting teleconference with Mr. Thomas McCurdy of the EPA regarding the CHAD database scrubbing rules (Jun. 6, 2010).

U.S. Department of Health and Human Services, Centers for Disease Control and Prevention, “2009 National YRBS Data Users Manual,” Manual for data collection and editing (2009).

U.S. Census Bureau, “ACS Design Methodology. Chapter 10: Data Preparation and procession for Housing Units and Group Quarters,” Manual for data collection methods and data editing (2006).

C. Websites

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Maine Heath Cost, “Procedure Payments for the Insured,” *available at* http://www.healthweb.maine.gov/claims/healthcost/procedure_pricing_insured.aspx (last visited Oct. 12, 2010).

Maryland Workers’ Compensation Commission, “This is the Maryland Workers’ Compensation Commission Medical Fee Guide Maryland Specific Conversion Factor (MSCF)/Multiplier (COMAR 14.09.03)” *available at* http://www.wcc.state.md.us/PDF/MFG/MSFC_rate.pdf (last visited Oct. 14, 2010).

Minnesota Department of Labor and Industry, “Background about the relative value for fee schedule,” *available at* http://www.dli.mn.gov/WC/PDF/RVU_background.pdf (last visited Oct. 14, 2010).

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D. Other

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VI. CORRESPONDENCE

Letter from Andrea Y. Loh, to Sarah A. Wilson (Jun. 2, 2010).

Letter from Andrea Y. Loh, to Joe R. Whatley Jr. (Jul. 6, 2010).

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Letter from Geoffrey Sigler, to Robert J. Axelrod and W. Tucker Brown, Re: Dr. Foreman's "Production Roadmap" (Oct. 1, 2010).

Exhibit 4

**UNITED STATES DISTRICT COURT
DISTRICT OF NEW JERSEY**

)
)
IN RE: AETNA UCR LITIGATION) **MDL NO. 2020**
) **(No. 2:07-CV-3541)**
)
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**EXPERT REPORT OF DR. ROBIN CANTOR IN RESPONSE TO THE DECLARATION
OF STEPHEN FOREMAN, DATED NOVEMBER 24, 2010**

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I. Qualifications

1. My name is Robin Cantor. I am a Principal in the Alexandria, VA office of Exponent, Inc. I specialize in applied economics, environmental and energy economics, statistics, and risk management. I have a B.S. in mathematics from Indiana University of Pennsylvania with a specialization in statistics and a Ph.D. in economics from Duke University with a specialization in econometrics.
2. I previously submitted an expert report in this matter (“Cantor Class Certification Report”) on April 6, 2010, a responsive expert report (“Cantor Responsive Class Certification Report”) on May 24, 2010, and a responsive expert report (“Cantor Responsive Merits Report”) on November 10, 2010.¹ In this report, I am incorporating by reference the opinions expressed and analysis contained in my earlier reports. A more detailed discussion of my qualifications and curriculum vita are contained therein. A copy of my current curriculum vitae is contained in Attachment 1. My testimonial experience in the last four years is attached as Attachment 2. My current billing rate for this engagement is \$580/hour for analysis and testimony. Other Exponent staff members have also worked at my direction on this matter and they have been billed at rates ranging from \$85 to \$415/hour.

II. Assignment

3. I have been engaged by Gibson, Dunn & Crutcher LLP (“Counsel”) on behalf of its clients, Aetna Health Inc. PA, Corp., Aetna Health Management, LLC, Aetna Life Insurance Company, Aetna Health And Life Insurance Company, Aetna Health Inc., Aetna Insurance Company of Connecticut, and Aetna, Inc. (collectively, “Aetna” or “Defendants”)², to provide an expert opinion in the matters that have been consolidated as *In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation (MDL No. 2020)*.
4. Since submitting the Cantor Class Certification Report, the Cantor Responsive Class Certification Report, and the Cantor Responsive Merits Report, I received and reviewed the Declaration of Stephen Foreman submitted by Plaintiffs’ experts.³ I have been asked to review and offer opinions on the analyses and opinions contained in the Foreman Declaration.
5. In this MDL matter, Plaintiffs allege that (a) due to an inherent conflict of interest, the Ingenix Prevailing Healthcare Charges System (“PHCS”) Database (the “Ingenix Database”) of provider charge information was flawed in its construction and compilation, leading to systematically lower distributions of charges as reported in PHCS; and (b) when Aetna used these allegedly flawed data to determine the usual,

¹ See Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed Apr. 6, 2010) (the “Cantor Class Certification Report”); Updated Responsive Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed May 1, 2010) (the “Cantor Responsive Class Certification Report”); Responsive Expert Report of Dr. Robin Cantor, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 10, 2010) (the “Cantor Responsive Merits Report”).

² In this report, “Defendants” refers only to the referenced Aetna entities and no other parties.

³ See Declaration of Stephen Foreman, PhD, JD, MBA, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 24, 2010) (“Foreman Declaration”).

customary and reasonable rates (“UCR”)⁴ for determining reimbursement of out-of-network (“ONET”) services, Aetna’s reimbursement rates for ONET services were lower than they would have been if Aetna had used a data source that did not suffer from the alleged flaws in PHCS.⁵

6. In this response to Dr. Foreman’s declaration, I consider a number of additional analytical issues based on my review of his new analyses and work product and whether they change any of my prior opinions as contained in my earlier reports.
7. My opinions are based on my understanding of the information available to me as of the date of this report and my experience and training as an economist and statistician. In the event that additional relevant materials are made available to me or if Plaintiffs’ experts amend or supplement their reports, I will consider such information as necessary. I reserve the right to supplement or amend this report based upon any additional work that I might conduct or supervise from my review of such materials. The materials I considered for my analyses are listed in the footnotes of this report and/or in Attachment 3.

III. Summary of Findings and Opinions

8. Based on my review of the Foreman Declaration, additional analysis, and my training and experience as an economist and statistician, I have the following additional opinions about Dr. Foreman’s work as reported in his declaration:

In his latest declaration, Dr. Foreman has proffered two additional datasets that he has constructed from the contributor data. He uses these new datasets as his benchmarks for his analysis of PHCS percentile values. I have used publicly available commercial and government data on billed charges and percentile values as my benchmarks. Neither Plaintiffs nor their experts have contended that these data are affected by the conflict-of-interest and/or conspiracy allegations in this matter. In contrast, Dr. Foreman has used the contributor data that is processed for PHCS and made his own adjustments to derive benchmark percentile values that are neither commercially available nor independent of the alleged challenged conduct. In each of his reports and in the latest declaration, Dr. Foreman has produced different versions of his benchmark data with widely varying coverage of the Ingenix Database and with insufficient back-up materials to demonstrate reliability. In no case, however, has Dr. Foreman used data for his benchmark that are free of the flaws as alleged by Plaintiffs. Moreover, Dr. Foreman has made no attempt to use information from the commercial and government benchmarks (or any other source that has been tested independently or is scientifically reliable) to test the reliability of his preferred benchmark data. Rather, the Foreman Declaration repeats his previously stated concerns about the commercial benchmarks and adds some additional opinions that are incorrect. I addressed Dr. Foreman’s core concerns about the commercial and

⁴ Aetna defines the reasonable and customary amount as “the prevailing charge for the service or supply in the geographic area where it is furnished.” See AET-C00103216. As was described in more detail in paragraph 25 of the Cantor Class Certification Report, the terms of Aetna’s plans vary, and reimbursement for ONET claims may be based on UCR, reasonable, usual and customary or prevailing charge plan language.

⁵ See Joint Consolidated Amended Class Action Complaint and Demand for Jury Trial, In re Aetna, Inc., Out-Of-Network “UCR” Rates Litigation (MDL No. 2020 filed Jul. 1, 2009) (the “Complaint”) at ¶ 1.

government benchmarks in earlier reports and here I have expanded my analysis of the available external benchmarks to address his continuing remarks.

9. In this report, I show that Dr. Foreman's measure of the alleged bias is a flawed metric to determine the merits of Plaintiffs' allegations. Dr. Foreman uses a metric based on a percent difference to investigate the alleged bias of the PHCS percentile values. Further analysis with Dr. Foreman's latest data demonstrates that the definition of the metric matters for any conclusions about systematic downward bias. By construction, the percent difference is a scale-free measure that uses either the benchmark value or the PHCS value in its denominator. The scientific literature on systematic bias indicates that the benchmark value should be used in the denominator and I have followed this definition for my analysis. In contrast, Dr. Foreman has departed from this scientific convention. I prove mathematically and demonstrate through simulations of randomly generated differences that Dr. Foreman's measure is biased and that percent difference measures can lead to substantially different findings from the Scientific Literature Metric and this difference is shown in Table 1 for the 5000 Study comparisons.

Table 1: Comparison of Percent Difference Methods – Foreman 5000 Study 2007

Contributor Year ¹	PHCS Release	Analysis	Scientific Literature Metric ²	Foreman Metric ³
2007	2006_1	Claim Weighted	-48.0%	19.1%
		Revenue Weighted	-59.6%	19.7%

Notes:

1. Data for 5000 Study sourced from: Excel File "compare_2007_1.csv". This file contains the above comparison between the 2007 contributor data and PHCS 2006 R1 and is the only 5000 Study production file turned over by Dr. Foreman.
2. Scientific Literature Metric is calculated as (Contributor-PHCS)/Contributor.
3. Foreman Metric is calculated as (Contributor-PHCS)/PHCS.

10. Dr. Foreman's results have been magnified by his choice of a biased metric. Consequently, in this report I have examined a related metric based on the matched-pair differences that averages the benchmark and the PHCS value for the denominator. I show that mathematically this measure mitigates the bias in the Foreman Metric. Using but not adopting Dr. Foreman's newest dataset based on the contributor data, I show that when the Average metric is used, claim-weighted PHCS values are not biased downward on average or across the board.
11. Dr. Foreman also mistakenly believes that values based on low claim count or derived values are “essentially random”⁶ and “bear no relationship to contemporaneous medical services in the market.”⁷ I show in this report that PHCS percentile values for low claim count CPT/geozip combinations or derived values are highly correlated with the commercial and government benchmarks. My findings fail to support Dr. Foreman’s

⁶ See Foreman Declaration at ¶ 5.

⁷ See Foreman Declaration at ¶ 13. Dr. Foreman's references to randomness in the percentile values are also found in ¶¶ 42, 43, 107, 118, 267, and 311.

opinions about the randomness of the values found in these combinations. This is of some consequence for Dr. Foreman's damages methodology. He uses the assertion that the values in low claim count or derived value combinations are random to justify setting the "accurate" allowed amount but for the challenged conduct to the actual billed charge to calculate damages.

12. The new work product from Dr. Foreman made available to me contains considerable errors that were identified previously by me and other experts in this matter. As a result, I find that the new work product from Dr. Foreman continues to have reliability problems that make any conclusions that he reaches based on his constructed percentile values suspect.
13. My prior opinions were based largely on analysis of external and independent data sources to investigate the alleged bias of PHCS values. Plaintiffs' experts have criticized the external data sources for various reasons. Since the submission of the Cantor Responsive Expert Report, however, FAIR Health has released additional information on its methods to manage and compile the billed charge data. I have conducted additional analysis of the methods FAIR Health uses to remove outlier data. I have also obtained the dental and medical/surgical data released by FAIR Health in 2011.
14. The procedures adopted by FAIR Health to manage outliers follow other standard methods used to manage information in large databases. The observation that FAIR Health has independently adopted a procedure to remove outliers from the compiled data has implications for the measurement of bias and damages in this matter. My analysis demonstrates that if these procedures remove outlier data, then they will have a tendency to reduce percentile values to a degree greater than the Ingenix high-low screen that is criticized by plaintiffs' experts. As I showed previously, and unlike the FAIR Health screen, the Ingenix high-low screen can increase percentile values in the post-screen data. FAIR Health's decision to adopt an outlier management procedure that acts to reduce the influence of large suspect values is not surprising. It suggests, however, that Dr. Foreman's benchmark data, in which no outliers are removed, are unlikely to be a proper benchmark for the percentile values but for the challenged conduct. If he had adopted a procedure at least as prudent as the FAIR Health rule, then some and perhaps many of his percentile values would be reduced. Because he makes no adjustment for outliers, comparisons between PHCS and Dr. Foreman's benchmarks will not reliably indicate the existence or amount of an alleged bias and are unsuitable as a basis for dependably measuring any damages.
15. In addition, the FAIR Health billed charge data do provide yet another source of percentile values independent of the Ingenix methods of data compilation and processing and are based on large numbers of contributor claims. Time-adjusted comparisons between the FAIR Health values and PHCS fail to support the large estimates of downward bias proffered by Dr. Foreman and are similar to what I previously measured with the commercial and government benchmarks.

IV. Bases for Opinions

A. Dr. Foreman's Declaration Fails to Remedy the Flaws in His Earlier Analyses

16. The Foreman Declaration purports to be a response to criticisms by Defendants' experts of the Foreman Merits Report.⁸ Specifically, Dr. Foreman states that he addresses criticisms about the processing of the contributor data to derive percentile values and his analyses based on the 300 and 350 Studies. But instead of correcting his acknowledged errors in those studies, the Foreman Declaration presents two additional databases that Dr. Foreman constructs from the contributor data. The "500 CPT Study" and the "5000 CPT Study" are expanded versions of the contributor datasets that Dr. Foreman used previously. His measure of bias continues to be based on the aggregate average percent difference between the percentile values that he estimates for each of his benchmark databases and the percentile values in PHCS.
17. Dr. Foreman reports that his 500 CPT Study was conducted using contributor data from 2006 - 2008. He states that he selected the 500 most common medical & surgical CPTs from 2007 data, used "all 421 geozips,"⁹ and that percentiles created from his contributor databases are compared with Ingenix percentile values.¹⁰ For each year of contributor data percentiles that he creates, Dr. Foreman reports percent differences for comparisons to three separate PHCS releases. Additionally, he makes comparisons with and without observations that have fewer than 255 claims.¹¹ Dr. Foreman reports that he finds downward bias in all of the claim-weighted average percent differences for the 80th percentile comparisons, ranging from 12 percent to 28.3 percent, and that these findings "verify and confirm" the results of his earlier "300 CPT" and "350 CPT" Studies.¹²
18. Dr. Foreman also processed the contributor data to compile a 5000 CPT Study dataset. Although Dr. Foreman continues to argue that CPT/geozips with fewer than 255 claims have sample sizes that are too small to estimate percentile values reliably, he drops this restriction in his 5000 CPT Study. Dr. Foreman's 5000 CPT Study is reportedly based on 5000 medical & surgical CPTs with at least 9 claims, and includes "all 421 geozips"¹³ from 2006 - 2008 Contributor data. Dr. Foreman again compares each year of his percentile values to three separate PHCS releases. Dr. Forman reports that the Study finds downward bias in all of the claim-weighted average percent differences for the 80th percentile comparisons, ranging from 5.5 percent to 21.4 percent.¹⁴ In this report, I

⁸ See Expert Report of Stephen Foreman, Ph.D., J.D., M.P.A., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) (the "Foreman Merits Report").

⁹ See Foreman Declaration at ¶¶ 157 & 162. As discussed in section E.1 and noted in Table 18, Dr. Foreman does not appear to include secondary geozips in his analysis.

¹⁰ Dr. Foreman states that the Ingenix data was obtained from the supporting materials filed by Dr. Monica Noether with the Responsive Expert Report of Monica G. Noether, Ph.D. dated November 10, 2010. See Foreman Declaration at ¶ 158.

¹¹ Dr. Foreman notes that he did not control for units in this particular analysis. See Foreman Declaration at ¶ 160.

¹² See Foreman Declaration at pp. 30 & 31; Deposition Transcript of Dr. Stephen Foreman (Oct. 11, 2011) (Rough) ("Foreman Deposition") at pp. 148-149.

¹³ See Foreman Declaration at ¶¶ 157 & 162. I address below the almost equal number of geozips that Dr. Foreman apparently is ignoring in his 5000 Study data.

¹⁴ See Foreman Declaration at p. 32. These values are taken from the table on p. 32 of the Foreman Declaration;

provide analysis of the percent difference metric that is the basis for Dr. Foreman's results to show that his inferences about bias are influenced by his selected calculation.

19. Some of the results presented in the Foreman Declaration reinforce analysis and findings that have been made by Defendant's experts. An important example is his reported frequencies for comparisons when the benchmark data are greater than PHCS. Dr. Foreman's table is reproduced in Figure 1. Even without correcting Dr. Foreman's errors, in every case considered, the results show that the benchmark is sometimes greater, equal to, or less than the matched PHCS value. These results show that PHCS is often equal to or greater than the benchmark and fail to support an across-the-board downward bias. They also show that the proportion of comparisons for which the benchmark is greater than PHCS falls substantially when a comparison is made for the closest time periods that are possible using the Foreman data.¹⁵ The comparisons of closer time periods are indicated in Dr. Foreman's results by rows in which the year of the contributor data is matched to the second release of PHCS for the same year, as in row 4 for example.

Figure 1: Foreman Declaration Frequencies

**5000 CPT Study
Qualitative Results
Weighted Average Percent Difference
Contributor Data and Ingenix PHCS
2006-2008 Contributor Data**

Contrib	Ingenix	greater	equal	less
2006	2005_1	58.8%	14.8%	26.3%
2006	2005_2	55.9%	18.0%	26.1%
2006	2006_1	51.9%	22.5%	25.6%
2006	2006_2	43.1%	32.5%	24.4%
2007	2006_1	60.3%	14.5%	25.2%
2007	2006_2	56.7%	17.5%	25.8%
2007	2007_1	53.1%	21.5%	25.4%
2007	2007_2	45.9%	30.0%	24.1%
2008	2007_1	60.3%	15.0%	24.6%
2008	2007_2	57.4%	17.8%	24.8%
2008	2008_1	54.2%	21.6%	24.2%
2008	2008_2	46.6%	30.0%	23.4%

Source: Foreman Declaration at p. 33.

however they do not match the values stated in ¶ 165 which immediately follows this table. In the Foreman Deposition, Dr. Foreman clarifies that he believes the numbers in ¶ 165 to be erroneous. See Foreman Deposition at pp. 60-61.

¹⁵ Note that even the comparison with the closest time periods presented by Dr. Foreman still is not truly contemporaneous. In all cases, Dr. Foreman compared his percentile values to Ingenix PHCS values that were based on contributor data from an earlier time period than Dr. Foreman used for his percentile values.

20. Similarly, Dr. Foreman admits in his declaration that comparisons using derived values for CPT/geozips with fewer than nine claims produced lower percentile values some of the time and higher values some of the time.¹⁶ Nonetheless, he interprets this result as a confirmation that the derived data bear no relationship to external billed charges: “[a]s noted in other portions of the Report (and this response) reporting values with very small numbers of claims (nine to 255) produce essentially ‘random’ results.”¹⁷ I show below that standard statistical analysis of the data indicates a systematic relationship between the commercial benchmarks and PHCS values from the derived or low claim count combinations. My findings fail to support Dr. Foreman’s interpretation of the data.
21. In his declaration, Dr. Foreman continues to argue against the elimination of outliers from the contributor data when creating the percentile values.¹⁸ He states that since percentiles are robust to outliers, there is no need for what he describes as “arbitrary” data elimination. Dr. Foreman provides no systematic review of large database management protocols as a basis for these opinions. I previously addressed standard practices used for large database management in my prior reports.¹⁹ In this report, I review the outlier procedures that have been reported in connection with the database development by FAIR Health. The FAIR Health procedure provides another independent example of data scrubbing in large databases that fails to support Dr. Foreman’s view on the treatment of outliers.
22. The Foreman Declaration repeats and expands his criticisms of the commercial and government benchmarks for billed charge values used previously by me and other experts in this matter. A number of his criticisms, however, are based on misinformation. Some examples: Dr. Foreman mistakenly believes that Wasserman’s Physicians’ Fee Reference (“PFR”) does not provide geozip-level geographic adjustment factors. As stated in the introduction of PFR’s User’s Manual, PFR multipliers are national references. “To adjust these national references for your area we have provided a list of 3 digit zip code prefix adjustment factors (multipliers).”²⁰ Dr. Foreman mistakenly believes that PMIC does not report percentile values. Not only does it report 50th, 75th, and 90th percentile values, but also it titles them “UCR”.²¹ Dr. Foreman asserts that I had no foundation for the PHCS percentile values to match to MAG High. Appendix C in the Cantor Responsive Report demonstrates that the MAG High values most closely align with the 85th percentile of PHCS. Finally, Dr. Foreman mistakenly believes that Medicare and PMIC carrier localities cannot be redefined reliably for comparisons to PHCS geozips. CMS, however, provides a “Zipcode to Carrier Locality” file which is “primarily intended to map Zip Codes to CMS carriers and localities”²² and can be used to map the areas into geozips.

¹⁶ See Foreman Declaration at ¶ 104.

¹⁷ See Foreman Declaration at ¶ 107.

¹⁸ See Foreman Declaration at ¶ 63.

¹⁹ See Cantor Responsive Merits Report at Sections D.1 & D.2.

²⁰ See Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2007. *Physicians’ Fee Reference 2007*. Milwaukee, WI: Yale Wasserman, D.M.D. Medical Publishers, Ltd. 2008 at p. 353.

²¹ See Practice Management Information Corporation. 2007. *Medical Fees in the United States 2007*. Los Angeles, CA: Practice Management Information Corporation at p. 29.

²² See Centers for Medicare & Medicaid Services, “Prospective Payment Systems – General Information,” available at http://www.cms.gov/ProspMedicareFeeSvcPmtGen/01_overview.asp (last visited Mar. 25, 2011).

23. The Foreman Declaration fails to address the criticism that Plaintiffs have not identified a benchmark that is a proper indication of PHCS values but for the so-called “cycle of collusion.” The benchmarks sponsored by Dr. Foreman continue to be subsets of the allegedly flawed data that are inputs to PHCS with large numbers of records removed by Dr. Foreman. Dr. Foreman has not proved that the removal of these records “corrects” the influences of the challenged conduct. He has not demonstrated that his proffered benchmarks reflect values that would exist in the world but for the challenged conduct. The Foreman Declaration contains no attempt to use the commercial and government benchmarks to test the validity of the values he calculates from the contributor data. In this report, I show that some of Dr. Foreman’s data that are most influential for his results are substantially inconsistent with the values in the commercial and government benchmarks. I also show that the data in the 500 and 5000 CPT Studies continue to suffer from the errors already identified by me and other experts regarding Dr. Foreman’s 300 and 350 CPT Studies. For example, contrary to Dr. Foreman’s claim in his declaration that he has evaluated the influence of considering units on percentile comparison results, his production data show that he has simply repeated the same error. In addition, he repeats the error in the compilation of data from batch geozips by again dropping the secondary geozips in the batch. I also find that with his new studies, Dr. Foreman arbitrarily eliminates other primary geozips that by his definition of the scope of the relevant data should be included. My analysis shows that in some cases he is eliminating nearly all the claims data for some states and a large percent of the claims data in populous states including California, New York, Pennsylvania, and Texas. As a result, the studies proffered by Dr. Foreman in the declaration are again rife with mathematical and processing errors making them unsuitable to remedy the flaws in his first attempts to estimate the alleged bias or measure damages.

B. Dr. Foreman’s Metric for Generating Aggregate Average Percent Differences Generates False Positives and Unreliable Results

24. Plaintiffs have alleged that “flaws” in the Ingenix Database led to lower percentile values and caused under-reimbursement for out-of-network claims where the Ingenix values were used by Aetna for making UCR determinations. To investigate whether this claim has merit, Plaintiffs’ experts must demonstrate that the alleged compilation and construction flaws result in percentile values for the upper percentiles that are “biased downward.”²³ Plaintiffs’ experts have focused their investigations on whether the Ingenix Dataset is “systematically understated,” implies “systematic suppression,” or leads to payments that display a “systematic downward bias.”²⁴ None of Plaintiffs’ experts rigorously define what they intend by the measure of the systematic effects or how they would demonstrate its reliability. One of Plaintiffs’ experts, however, has offered some conditions for its definition. In his deposition, Dr. Siskin testified that “[b]ias is when the expected value of the outcome is not equal to the true value” and “systematic”

²³ See Complaint at ¶ 180, bullet f.

²⁴ See Deposition Transcript of Dr. Bernard Siskin (Dec. 14-15, 2010) (“Siskin Deposition”) at 118; Expert Witness Report of Gordon Rausser, Ph.D., In Re: Aetna UCR Litigation (MDL No. 2020 filed Aug. 9, 2010) at ¶ 6; Foreman Merits Report at ¶ 19.

means “that it’s got a causal link to it.”²⁵ Dr. Siskin further stated that his definition of systematic is based on finding effects caused by a specific and purposeful methodology, process, or action at issue.²⁶ Another of Plaintiffs’ experts, Dr. Rausser, has stated that a “systematic” bias is a bias that is “non-random.”²⁷ An approach to aggregating the data that finds an overall average difference even where none actually exists – that is, where the observed effect is caused by the selected metric used to summarize bias across CPT/geozip combinations – presumably would not fit Dr. Siskin’s definition of systematic bias. Likewise, an approach to aggregating data that consistently produces positive percent differences even when random values are used presumably would not fit Dr. Rausser’s definition of a systematic bias. I show below such a situation has in fact been created by Dr. Foreman’s choice of the metric to measure systematic bias.

25. My further studies of Dr. Foreman’s benchmarks and his estimation of the alleged downward bias have revealed that Dr. Foreman’s selected percent difference metric – that is, the methodology that he uses for generating and aggregating average percent differences across the CPT/geozip combinations he studied – is unreliable and indicates an aggregate percent difference even when none exists. While Dr. Foreman concludes that a positive percent difference generated by his methodology indicates that there is a systematic downward bias in the Ingenix data, I show that Dr. Foreman’s methodology is designed in a way that generates false positives. Moreover, while Dr. Foreman concludes that his various studies “verify and confirm” each other because they all generate positive average percent differences, I show that Dr. Foreman’s methodology for generating average percent differences is skewed in a way that generates positive average percent differences even when random values are used in place of the Foreman benchmark. In short, a positive average percent difference generated by Dr. Foreman’s methodology does not reliably establish anything, because his methodology for aggregating the data distorts the results.
26. In this section I explain why his metric choice is magnifying the positive percent difference results he has been finding when comparing PHCS and his 300, 500, and 5000 Studies. I also demonstrate using some simple examples the positive bias of his metric. A formal mathematical proof and more extensive simulation studies are included in the Appendix. Based on this analysis, I conclude that Dr. Foreman has not produced an adequate analysis to prove that the PHCS values are systematically biased downward. In fact, I show that even his 5000 Study data fail to support the conclusions of his declaration.
27. By way of background, it is important to recognize that an investigation of the effects of the alleged systematic bias in the PHCS values requires a metric for analysis. Dr. Foreman and I are using what appear to be similar metrics for our investigations. Both of our metrics are based on the percent differences across matched-pair comparisons. Dr. Foreman’s most recent benchmark data, however, reveal that a subtle definitional difference between our metrics—the choice of data source for the denominator of the formula—is one factor leading to widely different analytical results from the comparisons. In his deposition, Dr. Foreman testified that either the Ingenix

²⁵ See Siskin Deposition at pp. 38-39.

²⁶ See Siskin Deposition at pp. 63-65 and 161.

²⁷ See Deposition Transcript of Gordon Rausser (May 20-21, 2010) at pp. 244-245.

value or his value can be used in the denominator when determining the difference between two values.²⁸ The choice of which value to use in the denominator of the formula, however, leads to diametrically opposed inferences about whether the Ingenix data are, on average, higher or lower than Dr. Foreman's data. In this section, I explain the nature of the difference between my analysis and the Foreman Metric and demonstrate the influence of each on the conclusions reached about the allegedly biased PHCS values. I also present analysis of an alternative metric that averages the values in the denominator and show that it supports my conclusions over those of Dr. Foreman.

1. The Source of the Bias in Dr. Foreman's Methodology

28. The metric used by Dr. Foreman to aggregate the average percent differences across CPT/geozip combinations places a greater weight on the observations for which the Foreman value is larger than the Ingenix value; and it places a smaller weight on the observations for which the Foreman value is less than the Ingenix value. When millions of observations are aggregated to generate an overall average – as they are in Dr. Foreman's results – this difference in weighting substantially impacts the results, to the point where the choice of one methodology or another can generate diametrically opposite results.
29. Dr. Foreman's methodology magnifies the effect of outlier observations where the Foreman value is much greater than the Ingenix value. In addition, his methodology does not correspondingly magnify the effect of outlier observations where the Foreman value is much less than the Ingenix value. This effect is extremely important in understanding Dr. Foreman's results, because his methodology for generating percentile values has generated a striking number of outlier observations – both high and low – in comparison to the Ingenix percentile values. His methodology for aggregating the data into overall averages places a massively greater weight on the high outliers than it does on the low outliers, which further skews his results.
30. Two simple examples illustrate the effects described above. In the first example, shown in Table 2, there are 20 hypothetical CTP/geozip combinations, each with a hypothetical PHCS 80th percentile value and each with a hypothetical benchmark 80th percentile value. In the first 10 CPT/geozip cells, the hypothetical PHCS value is less than the benchmark value by \$10. In the second set of 10 CPT/geozip cells, the PHCS value exceeds the benchmark value by \$10. Although, based on the symmetry across the 20 cells, we might expect that the average percent difference over the 20 comparisons would be zero, it is not based on the Foreman methodology for generating aggregate average percent differences. Using Dr. Foreman's methodology for these 20 CPT/geozip cells indicates that the benchmark values are, on average, 1 percent higher than the PHCS values. Based on Dr. Foreman's methodology, Dr. Foreman would apparently conclude that the PHCS values are systematically biased downward, when they clearly are not.

²⁸ See Foreman Deposition at p. 51.

Table 2: Hypothetical with Small Value Differences

CPT/geozip	PHCS Value	Benchmark Value	Foreman Metric ¹	Scientific Literature Metric ²
1	90	100	11%	10%
2	90	100	11%	10%
3	90	100	11%	10%
4	90	100	11%	10%
5	90	100	11%	10%
6	90	100	11%	10%
7	90	100	11%	10%
8	90	100	11%	10%
9	90	100	11%	10%
10	90	100	11%	10%
11	100	90	-10%	-11%
12	100	90	-10%	-11%
13	100	90	-10%	-11%
14	100	90	-10%	-11%
15	100	90	-10%	-11%
16	100	90	-10%	-11%
17	100	90	-10%	-11%
18	100	90	-10%	-11%
19	100	90	-10%	-11%
20	100	90	-10%	-11%
Mean	95	95	1%	-1%

Notes:

1. Foreman Metric calculated as (Foreman Value - PHCS Value)/PHCS Value.

2. Scientific Literature Metric calculated as (Foreman Value - PHCS Value)/Foreman Value.

31. Table 3 shows a second example in which comparisons with widely divergent but symmetrical values are used in the first two records, and the remaining cells have equal values. As with the first example, on a cell-by-cell basis the divergences are symmetrical, and there is no divergence in 18 out of 20 cells. This table clearly does not exhibit a systematic downward bias in the hypothetical PHCS values as compared to the hypothetical benchmark values. Nonetheless, using Dr. Foreman's methodology generates a conclusion that the benchmark values are, on average 490 percent greater than the PHCS values. Based on these results, Dr. Foreman would apparently conclude that the PHCS values are systematically biased downward and that it would be appropriate to award damages of 490 percent to all class members in all 20 CPT/geozip cells.

Table 3: Hypothetical with Large Value Differences

CPT/geozip	PHCS Value	Benchmark Value	Foreman Metric ¹	Scientific Literature Metric ²
1	1	100	9900%	99%
2	100	1	-99%	-9900%
3	100	100	0%	0%
4	100	100	0%	0%
5	100	100	0%	0%
6	100	100	0%	0%
7	100	100	0%	0%
8	100	100	0%	0%
9	100	100	0%	0%
10	100	100	0%	0%
11	100	100	0%	0%
12	100	100	0%	0%
13	100	100	0%	0%
14	100	100	0%	0%
15	100	100	0%	0%
16	100	100	0%	0%
17	100	100	0%	0%
18	100	100	0%	0%
19	100	100	0%	0%
20	100	100	0%	0%
Mean	95	95	490%	-490%

Notes:

1. Foreman Metric calculated as (Foreman Value - PHCS Value)/PHCS Value.

2. Scientific Literature Metric calculated as (Foreman Value - PHCS Value)/Foreman Value.

32. The source of the bias in Dr. Foreman's methodology is Dr. Foreman's metric for generating a percent difference for an individual CPT/geozip cell (what I call the "Foreman Metric"). Dr. Foreman has defined his metric as:

$$\text{Foreman percent difference in values} = \frac{\text{Benchmark} - \text{PHCS}}{\text{PHCS}}$$

33. The sign for Dr. Foreman's metric may be interpreted as follows:

- A positive percent difference indicates that the PHCS value is less than the benchmark value, and
- A negative percent difference indicates that the PHCS value exceeds the benchmark.

34. Inserting some hypothetical values into the Foreman Metric reveals the source of his bias. For example, if the Benchmark value is 100 and the PHCS value is 90, the Foreman

Metric generates a percent difference of +11 percent. That is, the Benchmark value is 11 percent greater than the PHCS value. The calculation is as follows:

$$\frac{\text{Benchmark} - \text{PHCS}}{\text{PHCS}} = (100 - 90) / 90 = 0.11$$

This calculation is reflected in lines 1 through 10 in Table 2. On the other hand, if the Benchmark value is 90 and the PHCS value is 100 (see lines 11 through 20 in Table 2), the Foreman Metric generates a percent difference of -10 percent. That is, the Benchmark value is 10 percent lower than the PHCS value. The calculation is as follows:

$$\frac{\text{Benchmark} - \text{PHCS}}{\text{PHCS}} = (90 - 100) / 100 = -0.10$$

35. The weighting in the Foreman Metric is particularly pronounced when there is a substantial difference between the Benchmark value and the PHCS value. Consider lines 1 and 2 in Table 3. If the Benchmark value is 100 and the PHCS value is 1, the Foreman Metric generates a percent difference of 9900 percent. That is, the Benchmark value is 9900 percent greater than the PHCS value. The calculation is as follows:

$$\frac{\text{Benchmark} - \text{PHCS}}{\text{PHCS}} = (100 - 1) / 1 = 99.00$$

On the other hand, if the Benchmark value is 1 and the PHCS value is 100 (see line 2 in Table 3), the Foreman Metric generates a percent difference of -99 percent. That is, the Benchmark value is 99 percent lower than the PHCS value. The calculation is as follows:

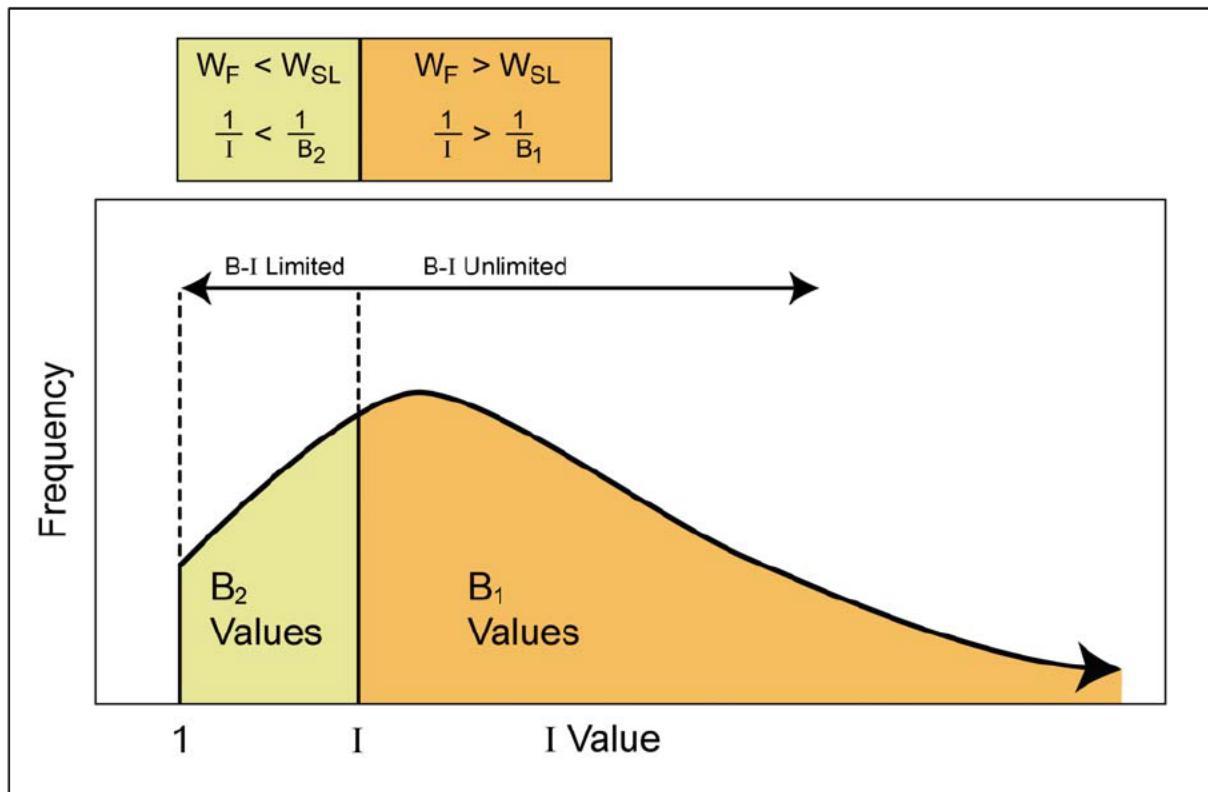
$$\frac{\text{Benchmark} - \text{PHCS}}{\text{PHCS}} = (1 - 100) / 100 = -0.99$$

The reason for these dramatic differences when one simply reverses whether the Benchmark or the PHCS value is the higher value is that the PHCS value is in the denominator of the equation. When the PHCS value is the smaller of the two values, the Foreman Metric is dividing a large number by a small number, which generates a large number as a result. On the other hand, when the PHCS value is the larger of the two values, the Foreman Metric divides a large negative number by a large number, which in this example generates a number less than one.

36. This mathematical property is illustrated in Figure 2. A distribution of values is shown that cannot be less than 1, but can extend to an arbitrarily large number. “I” is a selected value from the distribution of the 80th percentile values from PHCS, and “B₁” is a benchmark value that exceeds I, and “B₂” is a benchmark value that is less than I. The figure illustrates two important features of the Foreman Metric. First, the weight given to differences based on benchmark values to the right of I are greater under the Foreman Metric than under the Scientific Literature Metric, and conversely, the weight given to differences to the left of I are less under the Foreman Metric than the Scientific Literature

Metric. Second, the difference to the left of I is bounded by requiring that both I and the benchmark values be positive numbers greater than one. There is no similar bound to the right of I. The difference between I and the benchmark value could be very large, but the difference between I and the benchmark value when I exceeds the benchmark is not likely to be as large. I return to this point in ¶ 61 in the context of the 5000 Study data.

Figure 2: Properties of the Foreman Metric



- 37. The cumulative effect of this cell-by-cell approach when Dr. Foreman generates his aggregate average percent differences is that the CPT/geozip cells for which the Foreman value is greater typically will receive a greater weight than the CPT/geozip cells for which the PHCS value is greater (which in any case is bounded by -1). This effect is illustrated in Tables 2 and 3. When the percent differences across millions of matched pairs are aggregated (as Dr. Foreman has done in his studies), the effect of this weighting can be dramatic.
- 38. The Foreman Metric is not the only methodology to generate percent differences between observed data and a benchmark. And, significantly, it is not the accepted methodology in the scientific community. In my prior reports, I performed matched-pair analysis to investigate whether PHCS is biased downward systematically or across-the-board when compared to available benchmarks. I compared the upper percentile PHCS values with values from commercial benchmark products and the distribution average with the average value in Medicare PSPS. My analysis compared “matched” values for a

particular CPT in a particular geographic region. In order to normalize for scale, my comparisons were based on the percent difference in matched values—the same basic metric employed by the NYAG Report.²⁹ My original metric to measure the differences between the PHCS and benchmark values was defined as:

Metric for percent difference in values from

$$\text{Cantor Class Report} = \frac{\text{PHCS} - \text{Benchmark}}{\text{Benchmark}}$$

39. Each percent difference by CPT (or CDT) by geographic region yielded an observation for the benchmark comparison.
 - A negative percent difference indicates that the PHCS value is less than the benchmark value.
 - A positive percent difference indicates that the PHCS value exceeds the benchmark.
40. The metric that I used follows a standard definition for measuring the percent error between observed data and a benchmark or standard.³⁰ When measuring the percent error, the benchmark or standard is used in the denominator to reference the result as a percentage of the standard (referred to herein as the “Scientific Literature Metric”). For example, such measures are used by national and regional environmental protection agencies to signal compliance with air quality standards.³¹
41. To make the sign of the Foreman Metric and the Scientific Literature Metric consistent, the numerator in the equation can be standardized to Dr. Foreman’s formulation, that is, (Benchmark – PHCS). Thus, a positive percent difference results where the Benchmark value is greater and a negative percent difference results where the PHCS value is greater. This modification in the numerator has no effect on the equations, other than to the positive/negative sign of the output. I have adopted this formulation throughout the remainder of this report.

²⁹ See State of New York, Office of the Attorney General, “Health Care Report: The Consumer Reimbursement System is Code Blue,” (Jan. 13, 2009) (“NYAG Report”) at p. 20, Tables 2 & 3.

³⁰ See, e.g., Taylor, J.R. 1982. *An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements*, 2nd ed. United States: University Science Books.; Camalier L, Eberly S, Miller J, Papp M. Environmental Protection Agency. Guideline on the Meaning and The Use of Precision and Bias Data Required by 40 CFR Part 58 Appendix A. EPA-454/B-07-001. January 2007, available at <http://www.epa.gov/ttnamti1/files/ambient/monitorstrat/precursor/07workshopmeaning.pdf> (last visited June 29, 2011); Food and Agriculture Organization of the United Nations. Guidelines for quality management in soil and plant laboratories (FAO Soils Bulletin – 74), available at <http://www.fao.org/docrep/W7295E/w7295e08.htm> (last visited June 29, 2011).

³¹ See, e.g., Camalier L, Eberly S, Miller J, Papp M. Environmental Protection Agency. Guideline on the Meaning and The Use of Precision and Bias Data Required by 40 CFR Part 58 Appendix A. EPA-454/B-07-001. January 2007, available at <http://www.epa.gov/ttnamti1/files/ambient/monitorstrat/precursor/07workshopmeaning.pdf> (last visited June 29, 2011); Indiana Department of Environmental Management, Office of Air Quality. Chapter 13. Quality Assessment and Statistical Analysis of Air Monitoring Data, available at http://www.in.gov/idem/files/oaq_qa_manual_chap_13.pdf (last visited June 29, 2011).

2. Because Dr. Foreman's Methodology for Generating Aggregate Average Differences Is Biased, His Conclusions Are Unsupported and Unreliable

42. Dr. Foreman concludes that he has shown a systematic downward bias in the Ingenix PHCS data because his 300, 350, 500, and 5000 CPT studies all show a positive average percent difference between his percentile values and the Ingenix PHCS values.³² Similarly, he concludes that his various studies "verify and confirm" each other because they all show a positive average percent difference.³³

43. Dr. Foreman's conclusions, however, are sensitive to the choice of the methodology used to generate the aggregate average percent differences. In particular, switching from Dr. Foreman's methodology to the Scientific Literature Metric for generating aggregate average percent differences leads to the exact opposite conclusion. This is shown below in Table 4 for the claim- and revenue-weighted results.³⁴ Both the sign of the percent difference and its magnitude changed considerably depending on whether the benchmark or PHCS value is used in the denominator for the average percent differences.

Table 4: Comparison of Percent Difference Methods – Foreman 5000 Study 2007

Contributor Year ¹	PHCS Release	Analysis	Scientific Literature Metric ²	Foreman Metric ³
2007	2006_1	Claim Weighted	-48.0%	19.1%
		Revenue Weighted	-59.6%	19.7%

Notes:

1. Data for 5000 Study sourced from: Excel File "compare_2007_1.csv". This file contains the above comparison between the 2007 contributor data and PHCS 2006 R1 and is the only 5000 Study production file turned over by Dr. Foreman.

2. Scientific Literature Metric is calculated as (Contributor-PHCS)/Contributor.

3. Foreman Metric is calculated as (Contributor-PHCS)/PHCS.

44. As these results show, under the Scientific Literature Metric, there is no support for Plaintiffs' theory of downward bias in the PHCS values. Of course, because the Scientific Literature Metric uses the Foreman value in the denominator (instead of the Ingenix value, as in the Foreman Metric), the weighting effect from the Scientific Literature Metric is exactly the opposite as the weighting effect from the Foreman Metric. That is, CPT/geozip cells in which the Ingenix value is greater are given greater weight, and the CPT/geozip cells in which the Ingenix value is lower are given less weight.

45. Having shown that the aggregate average percent differences were sensitive to the choice of metric, I conducted additional studies to investigate (a) whether the Foreman Metric

³² See Foreman Deposition at pp. 89-90.

³³ See Foreman Declaration at ¶ 7.

³⁴ The results shown in Table 4 include in their calculation those CPT/geozip combinations from Dr. Foreman's benchmark that have percentile values less than \$1. Excluding these combinations from this analysis produces a claim-weighted result of 18.8 percent for the Foreman Metric and -1.1 percent for the Scientific Literature Metric.

can generate false positive values (as suggested by the hypothetical examples in Tables 2 and 3), and (b) whether Dr. Foreman is correct in concluding that his various studies “verify and confirm” each other because they all generate substantial positive results for the aggregate average percent differences using the Foreman Metric. To study these questions, I conducted a mathematical analysis of the percent difference metric, as described in the Appendix, that demonstrates that the expected value of the Foreman Metric is positive even when the expected value of the difference between the benchmark value and the PHCS value is zero. This analysis demonstrates that the Foreman Metric can generate false positives for the aggregate effect. In other words, when there is an aggregate average percent difference resulting from the Foreman Metric, it does not necessarily mean that there is any actual suppression in the Ingenix data.

46. In addition, to test Dr. Foreman’s hypothesis that his positive average differences for his various studies mean that the studies “verify and confirm each other” or somehow show that Dr. Foreman’s methodology for generating percentile values is reliable or consistent, I ran simulations using randomly generated deviated values in place of the PHCS data values. When I compared the Foreman benchmark to hundreds of thousands of values that differed only by a random deviation, my simulations consistently showed a substantial positive aggregate average difference using the Foreman metric – just like the results of the Foreman studies.³⁵ This study undermines any notion that merely producing a positive aggregate average difference using the Foreman Metric “verifies” or “confirms” either the reliability of the benchmark dataset or that there is any “systematic downward bias” in the Ingenix dataset. In this regard, it is significant to note Dr. Rausser’s explanation of what a “systematic” bias means. According to Dr. Rausser, a “systematic” bias is a bias that is “non-random.” If Dr. Foreman’s methodology for generating aggregate average differences can generate a substantial positive aggregate average difference even when the comparative values are randomly generated (as is consistently the case in the study that I conducted), then it follows that Dr. Foreman’s results showing a positive aggregate average difference do not support a reliable conclusion that there is a systematic downward bias in the Ingenix data. Dr. Foreman’s results, of course, do not *rule out* the possibility that there is a systematic downward bias in the Ingenix data, but at the same time they do not support a reliable conclusion that such a bias exists. Dr. Foreman’s results simply do not answer the question. The Appendix also contains a number of simulations demonstrating that variation in the distribution of values and a larger number of comparisons can increase the bias of Dr. Foreman’s metric.

³⁵ I also used PHCS as the “benchmark” and compared it to random deviations and the results regarding the metric biases were essentially the same.

3. Using Average Values in the Denominator Mitigates In Part the Influence of Dr. Foreman's Extreme Values

47. One approach to removing the influence of the selected denominator value is to use the average of the compared values as the reference for the percent difference. This approach is used when data are observed from two sources and neither source is considered an accepted standard or benchmark.³⁶ The objective of the comparison is not to measure bias (since there is no accepted standard) but rather to measure how much the data sources differ from each other on average. Tables 5 and 6 repeat the simple examples presented above and show that the Average Metric indicates that on average there is no systematic difference in the 20 hypothetical records.

³⁶ Environmental Protection Agency. Radon Glossary of Terms, *available at* www.epa.gov/radon/glossary.html (last visited June 29, 2011); Food and Drug Administration. Elemental Analysis Manual: Section 3.4 Special Calculations. Version 1 (June 2008), *available at* <http://www.fda.gov/Food/ScienceResearch/LaboratoryMethods/ElementalAnalysisManualEAM/ucm205119.htm> (last visited Oct. 25, 2011); Department of Ecology, State of Washington. Ecology Quality Assurance Glossary. *available at* http://www.ecy.wa.gov/programs/eap/qa/docs/QualityAssuranceGlossary_041410_final.pdf (last visited June 30, 2011); Defense Logistics Agency. Environmental, Safety and Occupational Health Management System. I Am The Key. Policies and Procedures. Programmatic Sampling and Analysis Plan, *available at* https://www.dnsc.dla.mil/iamthekey/UploadedFiles/GENERAL_Policies&Guidelines_psap_section_7_to_8.pdf (last visited June 29, 2011).

Table 5: Hypothetical with Small Value Differences – Average Metric

CPT/geozip	PHCS Value	Benchmark Value	Foreman Metric ¹	Scientific Literature Metric ²	Average Metric ³
1	90	100	11%	10%	11%
2	90	100	11%	10%	11%
3	90	100	11%	10%	11%
4	90	100	11%	10%	11%
5	90	100	11%	10%	11%
6	90	100	11%	10%	11%
7	90	100	11%	10%	11%
8	90	100	11%	10%	11%
9	90	100	11%	10%	11%
10	90	100	11%	10%	11%
11	100	90	-10%	-11%	-11%
12	100	90	-10%	-11%	-11%
13	100	90	-10%	-11%	-11%
14	100	90	-10%	-11%	-11%
15	100	90	-10%	-11%	-11%
16	100	90	-10%	-11%	-11%
17	100	90	-10%	-11%	-11%
18	100	90	-10%	-11%	-11%
19	100	90	-10%	-11%	-11%
20	100	90	-10%	-11%	-11%
Mean	95	95	1%	-1%	0%

Notes:

1. Foreman Metric calculated as (Foreman Value - PHCS Value)/PHCS Value.

2. Scientific Literature Metric calculated as (Foreman Value - PHCS Value)/Foreman Value.

3. Average Metric calculated as (Foreman Value - PHCS Value)/((Foreman Value + PHCS Value)/2)

Table 6: Hypothetical with Large Value Differences – Average Metric

CPT/geozip	PHCS Value	Benchmark Value	Foreman Metric ¹	Scientific Literature Metric ²	Average Metric ³
1	1	100	9900%	99%	196%
2	100	1	-99%	-9900%	-196%
3	100	100	0%	0%	0%
4	100	100	0%	0%	0%
5	100	100	0%	0%	0%
6	100	100	0%	0%	0%
7	100	100	0%	0%	0%
8	100	100	0%	0%	0%
9	100	100	0%	0%	0%
10	100	100	0%	0%	0%
11	100	100	0%	0%	0%
12	100	100	0%	0%	0%
13	100	100	0%	0%	0%
14	100	100	0%	0%	0%
15	100	100	0%	0%	0%
16	100	100	0%	0%	0%
17	100	100	0%	0%	0%
18	100	100	0%	0%	0%
19	100	100	0%	0%	0%
20	100	100	0%	0%	0%
Mean	95	95	490%	-490%	0%

Notes:

1. Foreman Metric calculated as (Foreman Value - PHCS Value)/PHCS Value.
2. Scientific Literature Metric calculated as (Foreman Value - PHCS Value)/Foreman Value.
3. Average Metric calculated as (Foreman Value - PHCS Value)/((Foreman Value + PHCS Value)/2)

48. I have applied this measure to the comparisons between the 5000 CPT Study data and the PHCS releases (specifically, the PHCS releases that are drawn from contributor data that is closest in time to Dr. Foreman's data). The results are shown in Table 7. Using the average values in the denominator, the claim-weighted percent difference is -0.5 percent and indicates that the data values do not differ substantially. This result fails to support Plaintiffs' theory that the Ingenix methods to process the contributor data ultimately suppress the percentile values reported in PHCS.

Table 7: Foreman Metric Compared to Average Metric

Comparison	Analysis	Foreman Metric	Average Metric
Foreman 5000 Study	Simple Average	35.9%	10.7%
	Claim Weighted	17.0%	-0.5%

Notes:

1. Foreman 5000 Study data sourced from Excel File "compare_2007_1.csv".
2. Foreman Metric computed as (5000 Study - PHCS)/ PHCS.
3. Average Metric computed as (5000 Study - PHCS)/((5000 Study + PHCS) / 2).

49. In summary, my analysis shows that Dr. Foreman's aggregate percent difference metric is not measuring a true bias in PHCS, and is influenced by his choice of the denominator for the metric. Using Dr. Foreman's metric, it is easy to demonstrate a positive percent difference not caused at all by a methodology or process used by Ingenix and therefore his findings fail to be consistent with either Dr. Siskin's or Dr. Rausser's definitions of systematic bias. In the next section, I show that in addition to the bias of his metric, Dr. Foreman's compiled datasets also contain many extreme and suspect data values that produce large positive percent differences for certain CPT/geozip combinations.

C. Dr. Foreman's Results Are Also Influenced by Extreme Values in His Benchmark Data That Lack Credibility

50. One factor influencing the difference in the calculated metrics is the mathematics of the formula. At the negative end, Dr. Foreman's Metric is bounded by -100 percent but can take on an infinitely large positive value with no upper bound. In contrast, the Scientific Literature Metric is bounded above by a positive 100 percent, and can be infinitely negative. Table 8 summarizes the bounds.

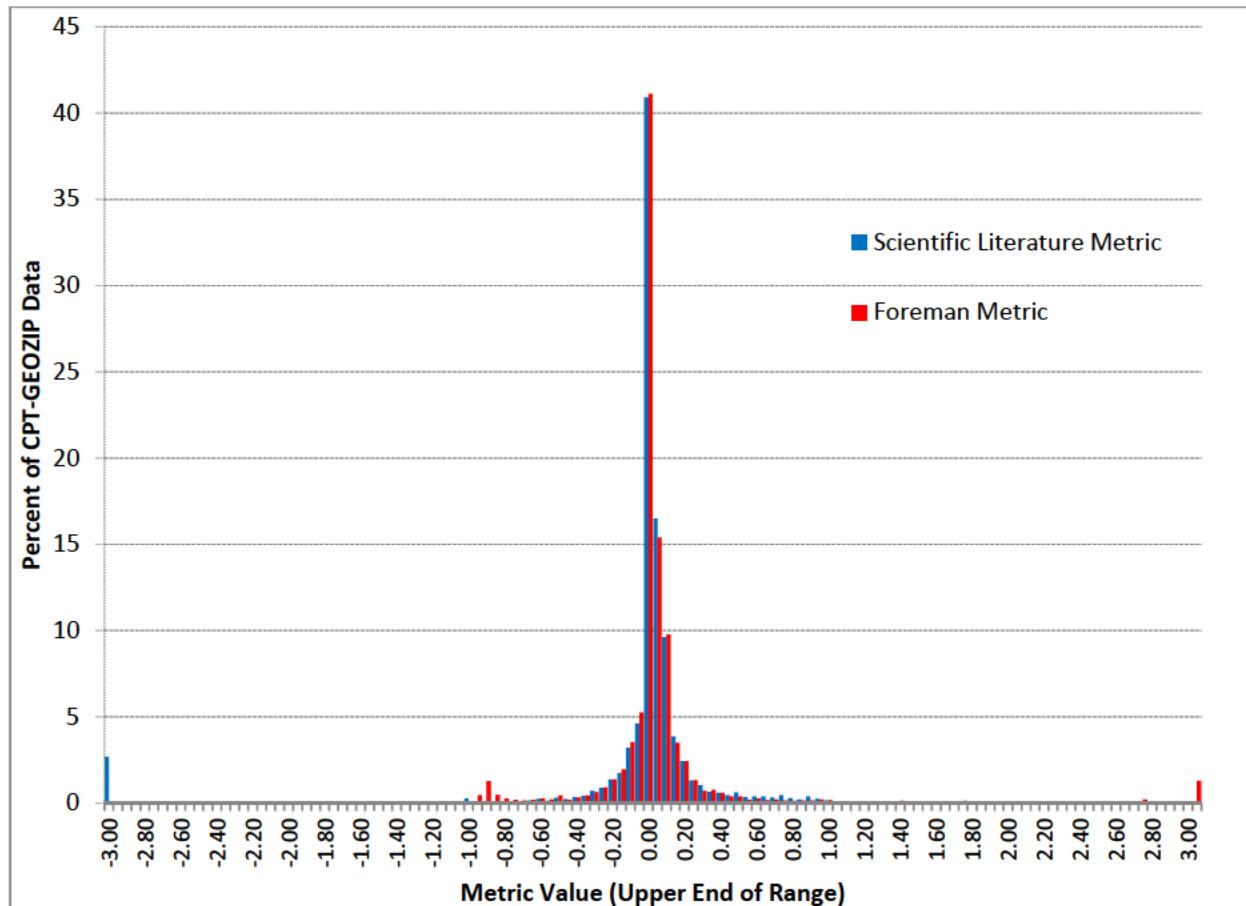
Table 8: Upper & Lower Bounds of the Percent Difference Metrics

	Upper Bound	Lower Bound
Scientific Literature Metric	1	$-\infty$
Foreman Metric	∞	-1

51. The bounds implied by the formula would be of little consequence for the percent difference results if the benchmark and PHCS values were similar for all or nearly all of the comparisons to the percentile values generated by Dr. Foreman. In that case, all of the percent differences would equal or be close to zero. Examining the distribution of results, the percent differences for the comparisons are largely concentrated around zero even when using but not adopting Dr. Foreman's 5000 CPT Study data, as shown below in Figure 3. The figure indicates that for a substantial proportion of the claims, the metrics agree and there are small or no differences between the 5000 CPT Study and the PHCS values. The figure also shows that both metrics indicate quite clearly that the

alleged downward bias is not across the board. To support that result, all the frequency in the figure would have been located above the zero value. Both the Foreman Metric and the Scientific Literature Metric show substantial frequency at the zero value and below.

Figure 3: Distribution of Claim-Weighted Percent Differences in Foreman 5000 CPT Study

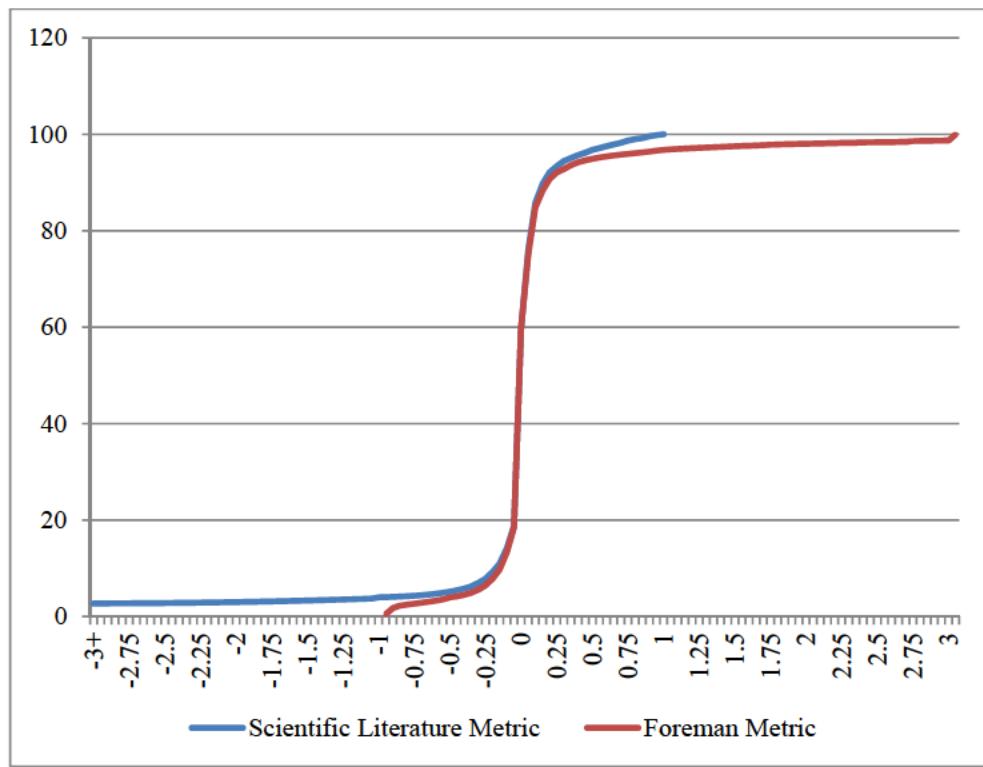


Notes: 1. Data greater than +3 or less than -3 is aggregated into data ranges from +2.95 to +3 and -2.95 to -3 respectively.

2. Claim weighted percent differences taken between Foreman 2007 5000 Study data (sourced from Excel File "compar_2007_1.csv") and PHCS2007R2.

52. The cumulative frequencies of the claim-weighted values using both the Foreman and the Scientific Literature Metrics are shown in Figure 4. Again it can be seen that for a substantial proportion of the data, there is little difference in the values of the two metrics. Most data fall near or at the zero value indicating no difference between the 5000 CPT Study 80th percentile value and the PHCS value regardless of the metric used.

Figure 4: Cumulative Distribution Functions of Claim-Weighted Percent Differences



Note: Claim weighted percent differences taken between Foreman 2007 5000 Study data (sourced from Excel File "compar_2007_1.csv") and PHCS2007R2.

53. Further investigation of Dr. Foreman's benchmark data reveals inexplicably high values for the upper percentiles of some of CPT/geozip combinations. I present analysis of some of these high values. I also examine comparisons with other benchmarks that suggest that these values are likely generated by errors in Dr. Foreman's methodology and/or reporting errors in the contributor data. Importantly, Dr. Foreman's metric magnifies the influence of these high (and potentially incorrect) percentile values in his estimate of bias. Dr. Foreman's benchmarks also contain inexplicably low values, but his metric formula suppresses the effect of these errors on his estimate of bias.
54. To understand the potential errors in the very high values in the Foreman 5000 CPT Study, I examined 100 of the potentially most extreme records. These 100 records are for the CPT/geozip combinations that have the largest differences between the benchmark and PHCS values (i.e., largest $B - I$). The maximum, minimum, and average values for these comparisons are shown in Table 9. There is more than a \$90,000 difference for the maximum record for which the PHCS 80th percentile value is \$3,500. On average for these comparisons, the Foreman benchmark value exceeds the PHCS value by approximately \$37,000.
55. I also examined information from the commercial benchmarks for these 100 comparisons. In one analysis, I extracted the 75th percentile value for these same 100 CPT/geozip combinations from PFR which is also shown in Table 9. The PFR values for the maximum and minimum comparisons are much closer to the PHCS values than they are to the Foreman benchmark. The average PFR value across the 100 records is almost

equal to the PHCS value and approximately \$27,000 less than the Foreman benchmark average.

Table 9: Summary Statistics for the Top 100 Positive Differences

	Max	Min	Mean	Standard Deviation
Foreman 75th Percentile	\$ 94,144	\$ 416	\$ 30,018	\$ 16,999
PHCS 75th Percentile	\$ 8,393	\$ 227	\$ 2,539	\$ 1,708
PFR 75th Percentile	\$ 7,457	\$ 418	\$ 2,811	\$ 1,705
Difference:				
Foreman 75th - PHCS 75th	\$ 90,644	\$ (1)	\$ 27,479	\$ 16,642
Difference:				
Foreman 75th - PFR 75th	\$ 87,558	\$ (562)	\$ 27,262	\$ 16,636
Foreman 80th Percentile	\$ 94,144	\$ 25,478	\$ 39,395	\$ 14,485
PHCS 80th Percentile	\$ 8,393	\$ 227	\$ 2,559	\$ 1,730
Difference:				
Foreman 80th - PHCS 80th	\$ 90,644	\$ 24,334	\$ 36,837	\$ 14,000

Notes:

1. PHCS data taken from PHCS 2007 R2.
2. Foreman 5000 Study data taken from "compare_2007_1.csv".
3. PFR data taken from PFR 2007.
4. Summary statistics shown are for the dataset that contains the 100 CPT/geozip combinations that have the largest positive absolute differences between the 80th percentile value presented in the Foreman 2007 5000 Study data and the 80th percentile value presented in PHCS 2007 R2.
5. The CPT/geozip combination that produces the maximum 80th percentile difference is REPAIR DETACHED RETINA (67108)/CA-SAN BERNARDINO,PALM SPRINGS (922-924).
6. The CPT/geozip combination that produces the minimum 80th percentile difference is REVISION OF UPPER EYELID (15823)/NY-AUBURN,LIVERPOOL (130-131).

56. Under the Foreman Metric, these 100 records yield a claim-weighted percent difference of 2,120 percent (in Table 11). In contrast, the same records yield a 93 percent claim-weighted difference using the Scientific Literature Metric. The substantial difference in the metric values is due to the choice of the denominator. By construction, Dr. Foreman's metric will always produce a more positive result for matched pairs that exhibit differences even when the PHCS value exceeds the benchmark.³⁷

57. The disparity observed above between values from the Foreman benchmark and PFR or PHCS persists over combinations of varying counts of claims. Table 10 presents the largest positive value differences for claim count between 9 and 39 claims, 40 to 254 claims, and 255 or more claims. When compared to the data from PHCS and PFR, the Foreman benchmark values appear inconsistent with the levels of the other values and

³⁷ In the case of $B(\text{enchmark}) > I(\text{ingenix})$, the numerator of both metrics, $B-I$, will be positive. As B is the larger of B and I , dividing this numerator by B will yield a smaller positive result than dividing by I . Therefore, $(B-I)/I > (B-I)/B$. In the case that $I > B$, both numerators will be negative. As I is the larger of the two in this case, dividing by I will yield a less negative result than dividing by B , and so again, $(B-I)/I > (B-I)/B$.

they demonstrate relatively larger increases between reported percentiles. For example, the increase between the 75th and the 90th percentile value in row 2 is more than 2100 percent. These large jumps in the values are seen even among the comparisons in the high claim count range. For example, not only does the 90th percentile value for CPT 64627 in row 8 appear very high relative to the PHCS and PFR values, it also reflects more than a 100 percent increase over the 75th percentile value from the Foreman benchmark.

Table 10: Largest Positive Value Differences by Claim Count Category

Claim Count Category ¹	Foreman		PHCS		PFR			
	CPT	Geozip	Percentiles ²		Percentiles ³			
			75th	90th	75th	90th		
9 to 39	67108	922	\$94,144	\$94,144	\$3,500	\$3,975	\$6,586	\$7,754
	69930	801	\$4,188	\$93,235	\$4,188	\$4,188	\$4,567	\$5,420
	63685	334	\$74,020	\$97,759	\$1,449	\$3,000	\$2,655	\$2,966
40 to 254	61885	770	\$46,738	\$64,800	\$1,500	\$1,695	\$1,608	\$1,852
	93613	405	\$36,253	\$55,220	\$501	\$501	\$1,151	\$1,315
	37205	700	\$32,756	\$47,323	\$2,100	\$2,320	\$2,062	\$2,490
Greater Than or Equal to 255	50590	850	\$11,800	\$25,421	\$1,570	\$2,500	\$3,635	\$4,359
Greater Than or Equal to 255	64627	770	\$9,205	\$26,550	\$500	\$525	\$409	\$483
Greater Than or Equal to 255	47562	808	\$16,772	\$16,772	\$1,800	\$3,183	\$2,781	\$3,134

Notes:

1. Examples are the top three CPT/geozip combinations in each claim count category when combinations are ranked by difference between Foreman 5000 Study 80th percentile value and PHCS 2007 R2 80th pernentile value from largest to smallest.
2. Foreman 5000 Study data taken from "compare_2007_1.csv".
3. PHCS data taken from PHCS 2007 R2.
4. PFR data taken from PFR 2007.

58. Large increases between the 75th and the 90th percentile values occur at an unusually high rate in the Foreman benchmark data. In the 5000 CPT Study, 46,311 combinations, or 10.6 percent of the data indicate more than a 100 percent increase from the 75th percentile value to the 90th percentile value. In contrast, neither the 2006 nor the 2007 PFR data have any occurrences where the 90th percentile value is 100 percent greater than the 75th percentile value. In 2006, PMIC has a very small percentage of records (0.06 percent) for which the 90th percentile value is 100 percent greater than the 75th percentile value.³⁸ For FAIR Health Dental, 0.56 percent of combinations have a 100 percent change or greater between the 75th and 90th percentiles. For FAIR Health Medical/Surgical, 2.01 percent of combinations have a 100 percent change or greater between the 75th and 90th percentiles.

59. I conducted similar analysis with the other commercial benchmarks. Although I used the same set of records (i.e., footprint) for my analysis, I used 2006 data for the PMIC and

³⁸ These records are for the same CPTs, 44950 – APPENDECTOMY and 50327 – PREP RENAL GRAFT/VENUS. 883 of the 886 records that make up this 0.06 percent are for CPT 44950 across most of the geozips.

MAG comparisons to 2006 PHCS due to the datasets available to me. The results were substantially the same and indicated that values in the Foreman benchmark for these 100 records were inexplicably high. Using but not adopting the Foreman Metric for the comparisons shows that the matched pairs across the commercial benchmarks yield percent difference results that are considerably lower than the results using the Foreman benchmark as shown in Table 11. For example, the claim-weighted percent difference between PFR and PHCS for these 100 records is 21 percent, which is two orders of magnitude less than the result based on the Foreman benchmark. The results using the Foreman benchmark are always larger than obtained with the commercial benchmarks both for the 100 records and for the entire Foreman 5000 CPT Study footprint.

Table 11: Foreman Metric Percent Differences within Related Datasets

Analysis	Comparison	Foreman Metric ¹ (% difference)	
		Top 100 ²	Entire Foreman Footprint ³
Simple Average	Foreman 5000 Study v. PHCS 2007 R2	2,351%	36%
	PFR 2007 v. PHCS 2007 R2	27%	18%
	MAG 2006 v. PHCS 2006 R2	34%	12%
	PMIC 2006 v. PHCS 2006 R2	48%	15%
Claim Weighted ⁴	Foreman 5000 Study v. PHCS 2007 R2	2,120%	17%
	PFR 2007 v. PHCS 2007 R2	21%	12%
	MAG 2006 v. PHCS 2006 R2	28%	12%
	PMIC 2006 v. PHCS 2006 R2	42%	7%
Revenue Weighted ⁵	Foreman 5000 Study v. PHCS 2007 R2	1,358%	11%
	PFR 2007 v. PHCS 2007 R2	10%	0%
	MAG 2006 v. PHCS 2006 R2	8%	0%
	PMIC 2006 v. PHCS 2006 R2	25%	1%
Price Weighted ⁶	Foreman 5000 Study v. PHCS 2007 R2	1,440%	36%
	PFR 2007 v. PHCS 2007 R2	9%	0%
	MAG 2006 v. PHCS 2006 R2	4%	-6%
	PMIC 2006 v. PHCS 2006 R2	20%	1%

Notes:

1. Foreman Metric is calculated as (Benchmark-PHCS)/(PHCS).
2. Comparisons done within the "Top 100" footprint. "Top 100" are the 100 CPT/geozip combinations with the largest value difference between Foreman 5000 Study 80th percentile and PHCS 2007 R2 80th percentile.
3. Comparisons done within the Foreman 5000 Study Footprint.
4. Claim Weighting done using PHCS 2007 R2 claim count taken from original PHCS release.
5. Revenue Weighting done using PHCS 2007 R2 claim count and PHCS 2007 R2 price taken from original PHCS release.
6. Price Weighting done using PHCS 2007 R2 price taken from original PHCS release.

60. The results above can be used to address some of Dr. Foreman's opinions about the alleged bias in high price and high revenue CPT/geozip combinations. In his declaration, Dr. Foreman suggests that finding a larger downward bias in the higher revenue

combinations would be “dispositive on the issue of downward bias...”³⁹ In the results above, however, revenue weighting reduces the measured downward bias (for all benchmarks, for the Top 100, and the entire Foreman footprint) compared to a simple average or claim weighting. In the entire Foreman footprint, revenue weighting produces no material bias at all for the commercial benchmarks. Similarly, price weighting reduces the measured bias relative to a simple average for the Top 100 for all benchmarks including the 5000 CPT Study. Price-weighted comparisons with the commercial benchmarks in the entire Foreman footprint yield essentially no downward bias and the result for the Foreman benchmark is unchanged from the simple average. Contrary to Dr. Foreman’s previously stated opinion about a positive relationship between prices and percent differences,⁴⁰ the 5000 CPT Study data for the entire footprint indicate no perceptible relationship between price and the measured percent difference. Standard correlation analysis using the 5000 CPT Study data confirms the results of the price weighting and indicates that the correlation between price and measured percent differences is small and negative.⁴¹

61. I also examined the top 100 negative value differences between the Foreman 5000 Study and PHCS. In these cases, the average difference shown in the last row of Table 12 is approximately \$6,000, which is one-sixth the magnitude of the average positive results shown above. Value differences between the Foreman benchmark and PHCS are truncated when the benchmark is less than the PHCS because no value (benchmark or PHCS) can be less than zero. This fact essentially limits the difference between a high PHCS value and the benchmark. In contrast, for the largest positive differences the benchmark values are not limited by how much they can exceed PHCS.

³⁹ See Foreman Declaration at ¶40.

⁴⁰ See Foreman Merits Report at ¶299 and Tables 17 & 18.

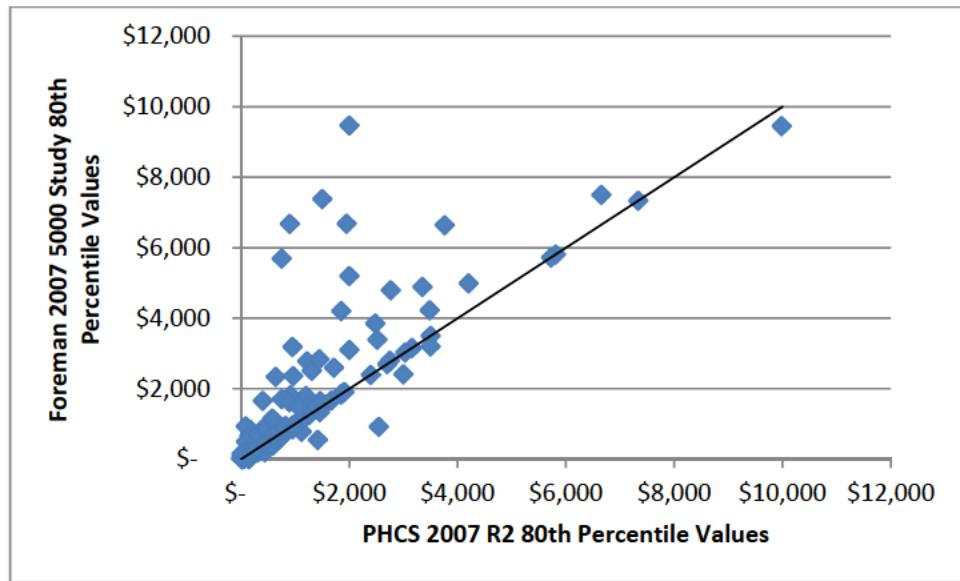
⁴¹ For the comparison of the Foreman 5000 Study 2007 contributor data to PHCS 2007 R2 the correlations between PHCS price and the Foreman simple average and claim-weighted percent differences are -0.001 and -0.013 respectively. PHCS price is not significantly correlated with the Foreman simple average percent difference. This correlation has a p-value of 0.6917. The correlation between PHCS price and the Foreman claim weighted percent difference is statistically significant with a p-value <0.0001.

Table 12: Summary Statistics for the Top 100 Negative Differences

	Max	Min	Mean	Standard Deviation
Foreman 75th Percentile	\$ 22,500	\$ 75	\$ 5,935	\$ 4,832
PHCS 75th Percentile	\$ 42,500	\$ 4,200	\$ 11,427	\$ 6,629
PFR 75th Percentile	\$ 17,358	\$ 1,371	\$ 6,315	\$ 2,190
Difference:				
Foreman 75th - PHCS 75th	\$ -	\$ (22,327)	\$ (5,492)	\$ 3,159
Difference:				
Foreman 75th - PFR 75th	\$ 2,952	\$ (6,361)	\$ (254)	\$ 3,989
Foreman 80th Percentile	\$ 26,442	\$ 75	\$ 6,223	\$ 5,246
PHCS 80th Percentile	\$ 42,500	\$ 4,836	\$ 12,324	\$ 6,803
Difference:				
Foreman 80th - PHCS 80th	\$ (4,085)	\$ (16,058)	\$ (6,101)	\$ 2,580
Notes:				
1.	PHCS data taken from PHCS 2007 R2.			
2.	Foreman 5000 Study data taken from "compare_2007_1.csv".			
3.	PFR data taken from PFR 2007.			
4.	Summary statistics shown are for the dataset that contains the 100 CPT/geozip combinations that have the largest negative absolute differences between the 80th percentile value presented in the Foreman 2007 5000 Study data and the 80th percentile value presented in PHCS 2007 R2.			
5.	The CPT/geozip combination that produces the maximum 80th percentile difference is LEFT HEART CATHETERIZATION (93510)/MD-SILVER SPRING,BETHESDA,GAITHERSBURG (208-209).			
6.	The CPT/geozip combination that produces the minimum 80th percentile difference is FOCUS RADIATION BEAM (61793)/NY-LEVITTOWN,BRENTWOOD,HAMPTON BAYS (117-119).			

62. Data “scatter” plots also illustrate the suspect patterns in the Foreman benchmark. In Figure 5, I have displayed the matched-pair coordinates for 300 randomly selected CPT/geozip combinations. If the Foreman 5000 Study percentile value equals the PHCS value for a combination, then the point would fall on the 45 degree line. The scatter plot shows that this is sometimes the case but there are many combinations for which the point is above the 45 degree lines and therefore indicates a higher value in the 5000 Study data.

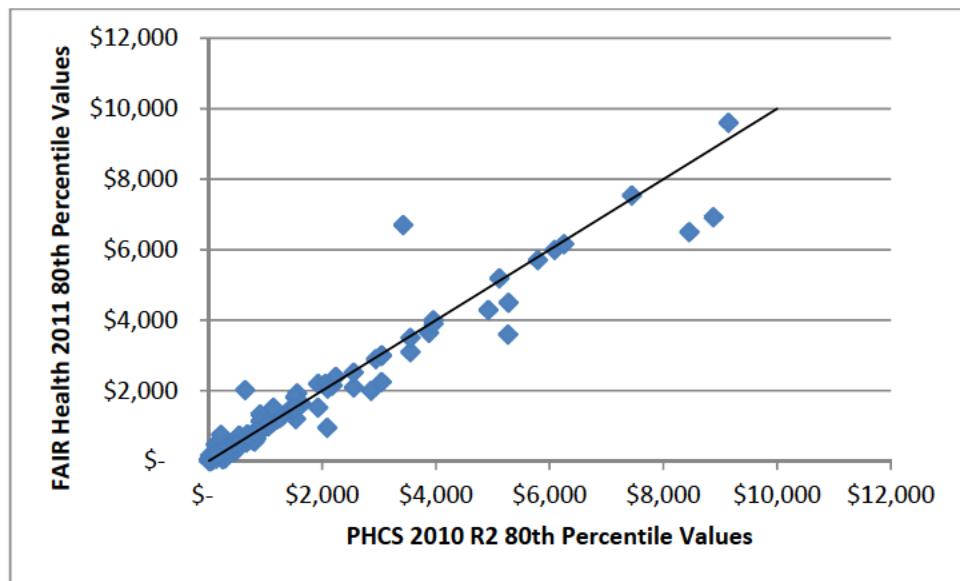
Figure 5: Foreman 2007 5000 Study Compared to PHCS 2007 R2



Note: The solid black upward-sloping line shows the points at which the Foreman values and PHCS values are equal.

63. I also randomly selected 300 combinations from the matched pairs for the FAIR Health and PHCS comparisons. Figure 6 displays this scatter plot which shows a very different pattern from the previous one using the Foreman benchmark. Most of the data points fall along the 45 degree line when the time-adjusted PHCS values are compared to the FAIR Health values.

Figure 6: FAIR Health 2011 Compared to Time-Adjusted PHCS 2010 R2



Notes: 1. The solid black upward-sloping line shows the points at which the FAIR Health values and PHCS values are equal.
2. PHCS 2010 R2 Medical/Surgical data range: Nov 2009 - Nov 2010; FAIR Health data range May 2010 - May 2011.
3. Time adjustments calculated as percentage difference between average monthly BLS CPI for Physicians' Services for FAIR Health data range and PHCS 2010 R2 ($334.876 - 329.924$) / 329.924 .

64. To summarize, the Foreman Metric is constructed to measure a more positive percent difference than the Scientific Literature Metric by using the PHCS value in the denominator. In addition, Dr. Foreman's benchmark data in the 5000 CPT Study have unusually high values when the benchmark exceeds the PHCS value and limited values when the benchmark is less than the PHCS value. This particular imbalance will exacerbate the measured differences between the Foreman and Scientific Literature Metrics. Using but not adopting the 5000 CPT Study data "as is" will magnify these influences and produces percent difference results that are not reliable.

D. Dr. Foreman's Theory on CPT/Geozip Combinations with Less Than 255 Claims Fails to Be Supported by the Data

65. In his declaration, Dr. Foreman claims that percentiles produced with derived data and those produced with empirical data consisting of less than 255 claims "tend[] to produce 'random' results."⁴² Although Dr. Foreman concedes that such values are not necessarily biased downward,⁴³ his perspective about this purported "randomness" is important to his damage methodology. Dr. Foreman measured damages for combinations with less than 255 claims using the billed charge amount as the amount "Aetna should have paid" but for the challenged conduct.⁴⁴ For combinations with more than 255 claims, Dr. Foreman measured damages with an "accurate" allowed amount that was based on his measure of

⁴² See Foreman Declaration at ¶ 311.

⁴³ See Foreman Declaration at ¶ 311.

⁴⁴ See Foreman Merits Report at ¶ 397.

bias. In the Cantor Responsive Merits Report, I criticized Dr. Foreman's treatment of damages for combinations with less than 255 claims because it assumes that the billed charge is the correct value but for the challenged conduct.⁴⁵

66. Although Dr. Foreman has asserted that percentile values for CPT/geozip combinations with less than 255 claims are "essentially random," he has offered no empirical analysis to support this conclusion. Notwithstanding Dr. Foreman's failure to offer such an analysis, the purported randomness of the low claim count and derived data can be tested directly with the available information. I have examined the correlation between PHCS percentile values and the benchmark values from derived and low claim count CPT/geozip combinations. If the derived and low claim count combination values are in fact random, correlations with the benchmarks should be close to zero. In contrast, results above 0.7 generally indicate a strong positive correlation.⁴⁶
67. Table 13 shows the results of my analysis of the correlations between PHCS data and other benchmarks including Dr. Foreman's 5000 CPT Study data. Across the different benchmarks, the derived data combinations show strong positive correlation with all of the results above 0.7. The correlations are even stronger using the combinations with claim counts between 9 and 254. Results for the low claim count combinations are all above 0.9. The last row of the table shows that the PHCS values and the values estimated by Dr. Foreman from the contributor data are also strongly correlated, but not as strongly correlated as the empirical PHCS values and the commercial and government benchmarks. As a point of reference, the correlation between the Foreman values from the 5000 CPT Study and PHCS for combinations with 255 claims or more is 0.89.

Table 13: Benchmark Correlations with PHCS

Benchmark ²	Derived ¹		Small Claim Count ¹	
	2006	2007	2006	2007
PFR - 75th Percentile	0.736	0.729	0.913	0.900
PMIC - 75th Percentile	0.747		0.907	
MAG - 85th Percentile	0.756		0.905	
Medicare PSPS - Mean	0.742		0.939	0.932
Foreman Contributor - 80th Percentile ³			0.752	

Notes:

1. "Small Claim Count" for this analysis refers to CPT/Geozip combinations with between 9 and 254 claims. "Derived" refers to CPT/Geozip combinations with fewer than 9 claims.
2. Sources for PHCS Data: PHCS 2006 release 2 and PHCS 2007 release 2.
3. "Forman Contributor - 80th Percentile" indicates a correlation at the 80th percentile of Dr. Foreman's 5000 Study Contributor Data for 2007.

68. These results indicate that there might be more variation in the CPT/geozip values based on derived data and low claim count combinations, but the values cannot be considered

⁴⁵ See Cantor Responsive Merits Report at ¶ 175.

⁴⁶ See, e.g., Cramer, D. 1997. *Basic statistics for social research: step-by-step calculations and computer techniques using Minitab*. New York: Routledge at p. 280.

random. Both the derived data and low claim count values tend to move together with other independent data on billed charges for the same set of CPT/geozip combinations. Dr. Foreman's assertion that these data are "essentially random" is not supported even using his constructed 5000 CPT Study benchmark for the correlation analysis.

E. Regardless of the Selected Metric or the Claim Count, Dr. Foreman's Data and Analyses Continue to Be Rife with Errors

69. Dr. Foreman's benchmark data contain values that indicate the continuing presence of methodological errors, data processing errors, and data reporting errors that affected his 300 and 350 CPT Studies data. In this section, I show that the choice of the denominator for the percent difference metric and the inclusion of the derived data are not the only factors causing the divergence of my results from those of Dr. Foreman. His benchmark data include percentile values less than \$1 that appear to be related to his error in the treatment of multiple unit records. In addition, there is information indicating that Dr. Foreman is repeating two other processing errors in the compilation of the Foreman benchmarks. First, not only has Dr. Foreman apparently made the error of dropping secondary geozips again, he also has dropped a substantial number of primary geozips without explanation. I show in this section that excluding many geozips and large number of claims produces differential impacts on the data represented for particular states. Second, I find again that Dr. Foreman's percentile values fail to match across his benchmarks for a substantial number of overlapping CPT/geozip combinations. Once again, Dr. Foreman's data and processing errors undermine the integrity of his constructed benchmark and its reliability for detecting and measuring the alleged bias.

1. Foreman Includes Large Numbers of Percentile Values Less Than \$1

70. Dr. Foreman's benchmark data continue to show large numbers of percentile values less than \$1 although this error was identified by me and other experts in our responsive merits reports.⁴⁷ These suspiciously low values include costs for vaccines and laboratory tests. The most common CPT codes in these records are related to allergy testing. CPT 95004 (Percutaneous allergy skin tests), 95044 (Allergy Patch Tests) and 95027 (Intracutaneous Allergy Test – Titrate/Airborne) and 95024 (Intracutaneous Allergy Test – Drug/Bug) constitute approximately 61 percent of the records.

71. Review of the data suggests that processed values less than \$1 could be due to an incorrect adjustment for records with multiple units. Dr. Foreman explains that for these records, he divided the billed charge amount by the number of units rather than expanding the number of claims by the number of units. Table 14 shows summary information about these claims. For those 744 CPT/geozip combinations in which the Foreman 80th percentile value is greater than zero and less than \$1, all of the commercial benchmarks and Medicare PSPS have percentile values greater than \$1. The PHCS

⁴⁷ See, e.g., Cantor Responsive Merits Report at ¶¶ 56-57; Expert Report of Thomas R. McCarthy, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 10, 2010) (the "McCarthy Report") at ¶226; Responsive Expert Report of Monica G. Noether, Ph.D., Darlery Franco, et al. v. Connecticut General Life Insurance Co., et al. (filed Nov. 10, 2010) (the "Noether Report") at footnotes 224 & 446.

average 80th percentile across these records is \$35.71. The average Foreman 80th percentile value across these records is \$0.44.

Table 14: CPT/Geozip Combinations with Percentile Values Greater than Zero but Less than \$1

Benchmark	Percentile	Year	Count	Avg. Value	Min. Value	Max. Value
Foreman 5000 Study	80th Percentile	2007	744	\$0.44	\$0.0007	\$0.99
PHCS	80th Percentile	2006- R1	0	\$35.71	\$5.00	\$2,702
PFR	75th Percentile	2007	0	\$30.69	\$8.39	\$1,784
MAG	High ¹	2006	0	\$22.25	\$7.52	\$477.54
PMIC - all	75th Percentile ¹	2006	0	\$30.95	\$5.96	\$1,213.21
Medicare PSPS - all	Mean	2007	0	\$18.01	\$3.50	\$539.50

Notes:

1. Because multiple benchmark values match to a single CPT/geozip combination; the average value provided is the minimum of the range of these values.
2. 5000 Study Data sourced from Excel File "compare_2007_1.csv."
3. For commercial and government benchmarks, only values >\$0 are included.
4. 'Count' is a count of CPT/geozip combinations. There is a total of 604099 claims where Foreman's 80th percentile is greater than zero but less than \$1.

72. Examining the commercial and government benchmark data outside of the records in the table above but in the Cantor empirical footprint reveals that only Medicare has reported values less than \$1 in a small number of cases. Table 15 shows that Medicare had 19 records with less than \$1 values in the 2007 data. Dr. Foreman's benchmark has 1,573 such cases. Outside of Dr. Foreman's minimum value of \$0.001, the observed minimum values across PHCS and the commercial databases are \$1 or more, and in some cases, substantially more. Dr. Foreman's low values for more than 1,500 records are not credible and cast doubt on the reliability of his methodology.

Table 15: Counts and Minimum Values of Commercial Benchmark Values Greater Than Zero and Less Than \$1

Year	Benchmark ²	Count ¹	Minimum Value			
			Mean	75 th Percentile	80 th Percentile	High
2005	PMIC	0		\$5.23		
	MAG	0				\$6.22
	PHCS	0				\$2.00
2006	PFR	0		\$6.71		
	PMIC	0		\$5.22		
	MAG	0				\$7.52
	NDAS	0				\$16.78
	Medicare PSPS	39	\$0.12			
2007	PHCS	0				\$2.00
	PFR	0		\$8.39		
	NDAS	0				\$17.62
2007	Medicare PSPS	19	\$0.36			
	PHCS	0				\$1.00
	Foreman 5000 Study	1573		\$0.001		\$0.001

Notes:

1. Count of CPT/geozip combinations with a 50th, 60th, 70th, 75th, 80th, 85th, 90th, or 95th percentile less than \$1 and greater than zero.

2. All CPT/geozips within Cantor Empirical Footprint.

2. Dr. Foreman Incorrectly Eliminates All Secondary And Many Primary Geozips from His Analysis

73. Another error identified in Dr. Foreman's methodology for his merits report was the elimination of geozips listed second or later in the ordering of a batch geozip record.⁴⁸ My review of Dr. Foreman's production indicates that he has used the same faulty methodology to construct his 500 and 5000 CPT Studies. Table 16 shows that Dr. Foreman is eliminating between 427 and 502 secondary geozips and all of their associated billed charge information from his processed datasets.

⁴⁸ See, e.g., Cantor Responsive Merits Report at ¶ 55; Noether Report at ¶353 bullet 5 & footnote 460; McCarthy Report at ¶141 & footnote 207.

Table 16: Count of Geozips by Batch Geozip Order

Data	Primary Geozip Count	Secondary Geozip Count
Foreman Contributor 2006^{1,5}	421	0
PHCS 2006⁴	421	482
Foreman Contributor 2007^{2,5}	421	0
PHCS 2007⁴	448	455
Foreman Contributor 2008^{3,5}	416	0
PHCS 2008⁴	475	427

Notes:

1. 2006 Contributor Year 500 Study data sourced from Excel Files: "merge_2006_10.csv", "merge_2006_20.csv" and "merge_2006_30.csv". These Excel Files contain PHCS percentiles for releases 2005 R1, 2005 R2 and 2006 R1 respectively. 421 primary geozips is the number of primary geozips found in "merge_2006_30.csv" and is the highest number of primary geozips found in any of these three files.
2. Both the 500 and 5000 Study data provided contain percentiles derived from 2007 contributor data. 5000 Study Data sourced from: 2007 - Excel File "compare_2007_1.csv". 2007 Contributor Year 500 Study data sourced from Excel Files: "compare_2007_10.csv", "compare_2007_20.csv" and "compare_2007_30.csv". These Excel Files contain PHCS percentiles for releases 2006 R2, 2007 R1 and 2007 R2 respectively. 421 primary geozips is the number of primary geozips found in files compared to 2006 PHCS data and is the highest number of primary geozips found in any of these files.
3. 2007 Contributor Year 500 Study data sourced from Excel Files: "merge_2008_10.csv", "merge_2008_20.csv" and "merge_2008_30.csv". These Excel Files contain PHCS percentiles for releases 2007 R1, 2007 R2 and 2008 R1 respectively. 416 primary geozips is the number of primary geozips found in files compared to 2007 PHCS data and is the highest number of primary geozips found in any of these files.
4. Counts shown are for the first PHCS release of the stated year. Results are identical for R2.
5. Foreman 500 & 5000 Studies include Puerto Rico and the U.S. Virgin Islands. Cantor analysis is limited to the 50 U.S. States.

74. In addition to eliminating all of the information from the secondary geozips, my review of the 500 and 5000 CPT Studies data produced by Dr. Foreman indicates that he also eliminated primary geozips from consideration. Overall, I estimate that he eliminated as many as 59 primary geozips from a single year of contributor data based on his production files. Together, the combinations in these primary and secondary geozips represent a substantial number of claims and the elimination effects are disproportionate across states.

75. To demonstrate this, I have used the claim count from PHCS for the batch geozips and estimated the claim count associated with each geozip by its share of the population in the batch area. Table 17 shows that the largest number and shares of eliminated claim data are in the high population states of New York, Texas, Pennsylvania, and California. Overall, I estimate that Dr. Foreman eliminated information from approximately 218 million out of 751 million claims, or 29 percent of the PHCS claim count, from the 5000 CPT Study scope. This percentage far exceeds the seven percent of claims that

Dr. Foreman identifies as a problem in his criticisms of the high-low screen used for outliers.⁴⁹

Table 17: Foreman 5000 Study, Percent of Claims Dropped in Top Ten Highest Claim Count States

State	Dropped Claims	Total State Claims	Percent of Total Claims Dropped
NY	22,810,115	72,259,533	31.6%
TX	24,984,131	68,058,491	36.7%
PA	19,866,087	47,324,969	42.0%
CA	14,137,433	47,039,951	30.1%
NJ	8,751,965	43,569,540	20.1%
NC	6,581,746	43,141,612	15.3%
IL	5,557,138	41,273,559	13.5%
FL	6,861,736	39,280,242	17.5%
OH	7,744,880	38,904,781	19.9%
MA	3,274,199	28,636,769	11.4%
Top Ten	120,569,429	469,489,447	25.7%
All	217,714,247	750,777,443	29.0%

Notes:

1. PHCS data sourced from PHCS 2007 R2, Empirical claims only.
- Claims counts are adjusted by the population in their respective geographic area based on the U.S. 2000 Census. Dr. Foreman excludes all secondary geozips from his 5000 Study analysis.
2. Foreman 5000 Study data sourced from Excel File "compare_2007_1.csv".

76. Examining the top ten states for eliminated claims indicates that nearly all of the claims for certain states have been excluded from Dr. Foreman's benchmark. Table 18 shows that nearly all of the claims for Nevada have been removed from the Foreman benchmark. Across these top ten states, more than 68 percent of the claim information has been removed. Dr. Foreman's unjustifiable dropping of these claims from his studies is another factor demonstrating the unreliability of his methodology.

⁴⁹ See Foreman Declaration at ¶ 25; Foreman Deposition at pp. 323-325.

Table 18: Foreman 5000 Study, Percent of Claims Dropped in Top Ten States with Highest Percent Dropped

State	Dropped Claims	Total State Claims	Percent of Total Claims Dropped
NV	6,230,650	6,246,536	99.7%
WV	2,206,359	2,680,640	82.3%
IA	4,952,201	6,267,932	79.0%
WY	715,040	911,913	78.4%
PR	332,217	478,486	69.4%
ND	1,461,648	2,402,634	60.8%
LA	5,130,627	8,510,724	60.3%
VA	7,376,813	12,352,260	59.7%
KS	2,808,970	4,774,083	58.8%
AR	2,259,646	4,041,402	55.9%
Top Ten	33,474,171	48,666,610	68.8%
All	217,714,247	750,777,443	29.0%

Notes:

1. PHCS data sourced from PHCS 2007 R2, Empirical claims only.
Claims counts are adjusted by the population in their respective geographic area based on the U.S. 2000 Census. Dr. Foreman excludes all secondary geozips from his 5000 Study analysis.
2. Foreman 5000 Study data sourced from Excel File "compare_2007_1.csv".

3. Percentile Values for the Same CPT/Geozip Combinations Fail To Match Across the Foreman Benchmarks

77. In the Cantor Responsive Merits Report, I identified numerous records in Dr. Foreman's 300 and 350 CPT Studies data that failed to have equal percentile values for the same CPT/geozip combinations in the same year.⁵⁰ That same problem continues with his latest compiled benchmarks from the contributor data. Dr. Foreman is generating percentile values for a number of the same CPT/geozip combinations in the same time period; if his methodology for generating percentile values were reliable, the methodology would be expected to generate the same values for the same data. Dr. Foreman's failure to do so further demonstrates the unreliability of his methodology.

78. Table 19 shows that there are approximately 148,000 overlapping combinations in the 500 and 5000 CPT Studies. More than one third, or approximately 51,000, of these combinations have at least one percentile value that fails to match across the datasets. Of these, approximately 16,600 fail to match on the 80th percentile value and nearly 5000 combinations have more than a 20 percent difference in the reported 80th percentile values. For the group that exhibits at least a 20 percent difference, the average value in

⁵⁰ See Cantor Responsive Merits Report at ¶¶ 46-48.

500 CPT Study is more than \$444. This value is more than twice the approximately \$220 value for the 5000 CPT Study for the same CPT/geozip combinations.

79. I further investigated whether the reported differences were due to Dr. Foreman's treatment of multiple units in the claims data. The Foreman Declaration is vague about whether he corrected for units in the 500 CPT Study data. He states that he corrects for units in the 5000 CPT Study data. Because of Dr. Foreman's incomplete production of intermediate datasets and programs, I cannot determine all of the CPT/geozip combinations that would have been affected by Dr. Foreman's adjustment for multiple units from his limited production. I find, however, that only approximately 260 combinations of those failing to match on the 80th percentile value also had values less than \$1 so I am doubtful that this is the explanation for the discrepancies.

Table 19: Mismatched Percentiles by CPT/Geozip Combination, Foreman 500 v. 5000 Studies

Label	Description	5000 Study	500 Study
[A]	File Name	compare_2007_1.xls	compare_2007_10.xls
[B]	Total Observations per File	436,805	160,178
[C]	Count That Match on CPT/Geozip	147,959	
[D]	Of [C], Count That Don't Match on At Least One Percentile	51,059	
[E]	Of [C], Count That Don't Match on 80th Percentile	16,571	
[F]	Of [E], Count That Have 5000 Study 80th <\$1	262	
[G]	Of [F], Count That Also Have 500 Study 80th <\$1	2	
[H]	Of [C], Count with Percent Diff. >0 but <5	6,741	
[I]	Of [C], Count with Percent Diff. >=5 but <10	2,770	
[J]	Of [C], Count with Percent Diff. >=10 but <20	2,424	
[K]	Of [C], Count with Percent Diff. >=20	4,636	
[L]	Of [K], Mean 80th Percentile	\$219.84	\$444.48

Note:
1 Percent difference calculated as (5000 80th - 500 80th)/500 80th

80. To illustrate the diversity of the occurrences for which the 80th percentile values fail to match in the Foreman benchmarks for the same CPT/geozip combinations, I present the top 50 value differences in Tables 20 and 21. The occurrences are in many states and across various procedures. In addition, the table shows that large numbers of claims are associated with these conflicting values.

Table 20: 50 CPT/Geozip Combinations with Largest Value Differences between the Foreman 5000 and 500 CPT Studies

Geozip	CPT	State	PHCS 2006 R1 Batch Claim Count	PHCS 2006 R1 80 th Percentile	5000 Study Contributor Data 80 th Percentile	500 Study Contributor Data 80 th Percentile	Difference: 5000 80 th - 500 80 th
808	45384	CO	439	\$1,369	\$4,798	\$2,025	\$2,773
914	58558	CA	13	\$2,535	\$6,699	\$4,000	\$2,699
363	29881	AL	37	\$7,252	\$8,130	\$5,600	\$2,530
221	43235	VA	63	\$740	\$4,880	\$2,845	\$2,035
387	43239	MS	830	\$780	\$4,526	\$2,545	\$1,982
754	47562	TX	328	\$7,500	\$5,416	\$3,700	\$1,716
199	69436	DE	10	\$350	\$1,766	\$315	\$1,451
530	99296	WI	108	\$634	\$1,837	\$744	\$1,093
133	59510	NY	216	\$3,840	\$4,050	\$3,180	\$870
800	93510	CO	32	\$2,001	\$20,208	\$19,352	\$856
380	58558	TN	23	\$1,300	\$2,400	\$1,629	\$771
853	64484	AZ	24	\$440	\$2,616	\$1,847	\$770
160	93510	PA	46	\$1,279	\$9,807	\$9,056	\$751
547	58558	WI	22	\$1,960	\$3,879	\$3,140	\$739
856	69436	AZ	343	\$500	\$6,706	\$5,982	\$724
762	69436	TX	215	\$960	\$4,393	\$3,688	\$704
336	47562	FL	216	\$3,000	\$14,212	\$13,510	\$702
074	29881	NJ	312	\$2,958	\$9,248	\$8,584	\$664
722	47562	AR	128	\$2,968	\$8,560	\$7,899	\$661
126	58558	NY	37	\$2,500	\$6,119	\$5,492	\$627
757	59400	TX	223	\$3,050	\$3,800	\$3,228	\$572
117	47562	NY	825	\$3,500	\$13,000	\$12,433	\$568
716	29881	AR	68	\$3,025	\$2,994	\$2,428	\$565
166	55250	PA	78	\$550	\$1,750	\$1,200	\$550
277	31237	NC	88	\$651	\$1,259	\$749	\$510
609	42820	IL	18	\$1,081	\$6,287	\$5,791	\$496
605	66984	IL	334	\$3,000	\$5,686	\$5,220	\$466
915	55700	CA	20	\$350	\$1,050	\$600	\$450
376	69436	TN	53	\$891	\$3,281	\$2,839	\$442
707	66984	LA	547	\$2,600	\$7,708	\$7,280	\$428
306	47562	GA	276	\$2,346	\$11,030	\$10,602	\$428
563	29881	MN	249	\$2,763	\$4,274	\$3,850	\$424
602	11400	IL	66	\$250	\$810	\$393	\$417
065	19103	CT	74	\$905	\$6,839	\$6,432	\$407
954	58558	CA	111	\$1,130	\$5,721	\$5,318	\$403
239	43239	VA	286	\$700	\$2,422	\$2,027	\$396
701	36540	LA	222	\$50	\$20,278	\$19,883	\$395
338	20553	FL	43	\$146	\$671	\$281	\$390
967	43239	HI	137	\$1,598	\$2,461	\$2,081	\$380
534	29515	WI	12	\$105	\$658	\$280	\$378
902	62311	CA	116	\$750	\$3,125	\$2,765	\$360
609	66984	IL	95	\$2,200	\$5,518	\$5,170	\$347
460	64475	IN	155	\$635	\$1,841	\$1,502	\$339
336	69436	FL	302	\$425	\$5,378	\$5,042	\$336
940	43235	CA	133	\$899	\$1,510	\$1,175	\$335
707	20552	LA	387	\$160	\$936	\$606	\$330
275	31237	NC	220	\$1,259	\$1,068	\$749	\$319
270	29881	NC	314	\$2,600	\$5,248	\$4,929	\$319
638	45384	MO	189	\$974	\$2,722	\$2,408	\$314
323	47562	FL	192	\$2,900	\$13,395	\$13,099	\$296

Note:

Foreman Contributor data sourced from "compare_2007_1.xls" and "compare_2007_10.xls" for the 5000 study and 500 study respectively

Table 21: 50 CPT/Geozip Combinations with Largest Value Differences between the Foreman 500 and 5000 CPT Studies

Geozip	CPT	State	PHCS 2006 R2 Batch Claim Count	PHCS 2006 R2 80 th Percentile	500 Study Contributor Data 80 th Percentile	5000 Study Contributor Data 80 th Percentile	Difference: 500 80 th - 5000 80 th
636	90935	MO	90	\$123	\$21,762	\$1,674	\$20,088
736	90935	OK	61	\$300	\$19,446	\$1,389	\$18,057
164	90935	PA	286	\$400	\$18,057	\$1,389	\$16,668
184	90935	PA	640	\$176	\$18,057	\$1,389	\$16,668
360	90935	AL	68	\$200	\$18,057	\$1,389	\$16,668
470	90935	IN	247	\$320	\$18,057	\$1,389	\$16,668
936	90935	CA	156	\$358	\$18,057	\$1,389	\$16,668
467	90935	IN	392	\$198	\$17,875	\$1,550	\$16,325
460	90935	IN	230	\$350	\$17,050	\$1,550	\$15,500
186	90935	PA	366	\$350	\$16,668	\$1,389	\$15,279
313	90935	GA	295	\$150	\$16,668	\$1,389	\$15,279
837	90935	ID	36	\$250	\$15,249	\$663	\$14,586
954	90935	CA	251	\$418	\$14,586	\$663	\$13,923
475	90935	IN	492	\$300	\$15,279	\$1,389	\$13,890
970	90935	OR	10	\$218	\$15,125	\$1,375	\$13,750
434	90935	OH	25	\$380	\$14,300	\$1,100	\$13,200
130	90935	NY	93	\$200	\$13,616	\$1,047	\$12,569
801	90935	CO	188	\$328	\$13,890	\$1,389	\$12,501
808	90935	CO	299	\$156	\$12,022	\$1,389	\$10,633
210	90935	MD	156	\$139	\$11,178	\$1,389	\$9,789
786	90935	TX	668	\$500	\$11,050	\$1,389	\$9,661
609	90935	IL	53	\$311	\$9,900	\$825	\$9,075
270	90935	NC	417	\$216	\$8,818	\$678	\$8,140
983	90935	WA	659	\$69	\$8,229	\$633	\$7,596
382	90935	TN	370	\$225	\$8,250	\$1,375	\$6,875
230	58558	VA	213	\$850	\$7,383	\$756	\$6,627
956	90935	CA	82	\$146	\$7,383	\$1,389	\$5,994
855	69436	AZ	39	\$377	\$5,737	\$312	\$5,425
306	90935	GA	470	\$239	\$6,790	\$1,389	\$5,401
326	59510	FL	48	\$3,250	\$8,954	\$3,765	\$5,189
616	90935	IL	181	\$124	\$6,548	\$1,375	\$5,173
176	90935	PA	184	\$160	\$5,472	\$456	\$5,016
635	47562	MO	51	\$2,615	\$7,466	\$2,460	\$5,006
658	47562	MO	373	\$2,795	\$7,951	\$3,039	\$4,912
855	90935	AZ	63	\$350	\$6,875	\$2,150	\$4,725
910	90935	CA	46	\$315	\$5,000	\$400	\$4,600
392	47562	MS	310	\$1,658	\$9,030	\$4,500	\$4,530
952	42820	CA	90	\$900	\$7,775	\$3,372	\$4,403
297	47562	SC	48	\$3,001	\$8,670	\$4,380	\$4,290
286	58558	NC	138	\$1,340	\$6,151	\$1,950	\$4,201
683	69436	NE	160	\$409	\$4,669	\$510	\$4,159
335	19103	FL	205	\$1,005	\$8,305	\$4,153	\$4,153
613	90935	IL	44	\$300	\$5,500	\$1,375	\$4,125
910	69436	CA	23	\$684	\$8,064	\$4,032	\$4,032
469	90935	IN	164	\$580	\$5,200	\$1,300	\$3,900
493	90935	MI	311	\$330	\$5,193	\$1,298	\$3,895
970	47562	OR	62	\$1,775	\$7,105	\$3,285	\$3,820
170	90935	PA	295	\$1,216	\$5,152	\$1,389	\$3,763
086	64476	NJ	55	\$400	\$5,600	\$1,873	\$3,727
190	66984	PA	1378	\$3,000	\$7,641	\$4,000	\$3,641

Note:

Foreman Contributor data sourced from "compare_2007_1.xls" and "compare_2007_10.xls" for the 5000 study and 500 study respectively

81. Unexplained and unsupported data eliminations and data errors such as those identified here cast serious doubt on the processing methodology used to construct Dr. Foreman's benchmark datasets. It is particularly disturbing that these errors were previously identified and not addressed in the Foreman Declaration. I can see no reason to assign any greater level of analytical reliability to the 500 CPT and 5000 CPT Studies than I attributed to the 300 CPT and 350 CPT Studies. Those studies were so rife with errors that no reliable inferences could be reasonably based on their use as benchmarks to estimate the alleged biases in the PHCS values.

F. FAIR Health Analysis

82. Dr. Foreman has proffered his own versions of data benchmarks for comparison to the PHCS values, but he has yet to consider an independent benchmark for his bias analysis. He has criticized my studies based on the readily available commercial and government benchmarks for various reasons, including a supposed lack of transparency and representativeness of the underlying data.⁵¹ More recently, a new source of data has become available that addresses Dr. Foreman's criticisms of small claim counts, transparency, and outlier screening procedures.⁵² In 2009, the non-profit organization FAIR Health acquired ownership of Ingenix' PHCS and MDR claims databases. In 2011, FAIR Health began to license and to distribute its own claims databases, under the FH™ Benchmarks and FH™ RV Benchmarks product lines.⁵³ Databases formerly called "PHCS" by Ingenix are now called "FH" and Ingenix MDR databases are now called "FH RV."⁵⁴

83. FAIR Health reports that it intends to maintain the same release schedule used by Ingenix for its benchmarking database modules. For example, FH Dental modules are expected to be released in January and July of each year and FH Medical/Surgical modules are expected to be released in May and November.⁵⁵ FAIR Health has also reported on the methods it is currently using for managing outliers in the contributor data. I consider these methods in the context of the simulation I presented in the Cantor Responsive Merits Report to demonstrate how the FAIR Health methods compare to the application of the Ingenix high-low screen.

84. I obtained the January 2011 FH Dental Module and May 2011 FH Medical/Surgical Module in electronic format from FAIR Health. Although these data were released in 2011, I have examined the percentile values as benchmarks for the PHCS values but for the challenged conduct in the same way that I have used the other commercial and government data sources. Because the FH modules were released at different times than the Ingenix modules, I have adjusted for time differences. As with the other commercial and government sources, there is no foundation to believe that the FAIR Health data

⁵¹ See Foreman Declaration at ¶ 218; Foreman Deposition at pp. 229-230.

⁵² See Foreman Declaration at ¶¶ 216-218.

⁵³ See FAIR Health, "Letter from FAIR Health's President," available at <http://www.icontact-archive.com/aaeAnbeTqkYZaFrqTeqAzwU5KAWVjMrV#successfullaunch> (last visited Jun. 20, 2011).

⁵⁴ See FAIR Health, "FH™ RV and FH Benchmarks Release Schedule," available at http://fairhealthus.org/sites/fairhealthus.org/files/FAIR%20Health%20Product%20Release%20Schedule_0.pdf (last visited Jun. 20, 2011).

⁵⁵ *Ibid.*

would be influenced by the conflict of interest and conspiracy conduct alleged by Plaintiffs. I report the results of comparisons with recent and comparable PHCS data and also with the 300 Study data from Dr. Foreman's proffered benchmark for 2006 values.

1. FAIR Health Method to Manage Outliers

85. FAIR Health reports that it has made refinements to the methodology Ingenix used previously to clean raw claims data received from contributors, including a change to the way that it manages outliers. FAIR Health has discontinued the high-low screen used by Ingenix to eliminate the highest and lowest charges submitted by providers. In its place, FAIR Health:

[excludes] charges that fall outside four standard deviations of the mean value of charges for each procedure/service within each geographic region. The mean is calculated using data from the current year plus the previous five years. For purposes of calculating the mean, data from past years is trended forward to the current year using the medical services Consumer Price Index (CPI).⁵⁶

86. This FAIR Health screen has been implemented in data releases produced by FAIR Health prior to August 2011.⁵⁷ In subsequent releases, FAIR Health has updated its methodology for managing outliers.

This methodology, which was developed by the Upstate Health Research Network (UHRN) and approved by the FAIR Health Board, is based upon a median absolute deviation (MAD) technique that calculates outlier thresholds based on the median absolute deviation for each procedure within each geozip. In addition, certain products also implement an absolute minimum threshold that will flag and exclude charges falling below specific absolute minimum dollar values (e.g., one dollar) which indicate that the charges likely do not represent valid charges for independent medical services.⁵⁸

87. In the Cantor Responsive Merits Report, I presented the results of a simulation of the effects on the 80th percentile value of a right-skewed distribution from a classic Tukey screen ("Tukey"), Dr. Foreman's derivation of the Tukey screen as an approximation for the high-low screen ("Foreman"), and Ingenix's actual high-low screen ("high-low"). My simulation revealed that when the high-low screen is defined properly, it can sometimes decrease, increase, or leave unchanged the value of the 80th percentile for a

⁵⁶ See FAIR Health, "Summary of FAIR Health Phase I Rate Table Methodology, Addendum, March 2011," available at http://www.fairhealthus.org/sites/fairhealthus.org/files/Summary%20of%20FAIR%20Health%20Phase%20I%20Rate%20Table%20Methodology%20Addendum%20March%202011_0.pdf (last visited Oct. 25, 2011).

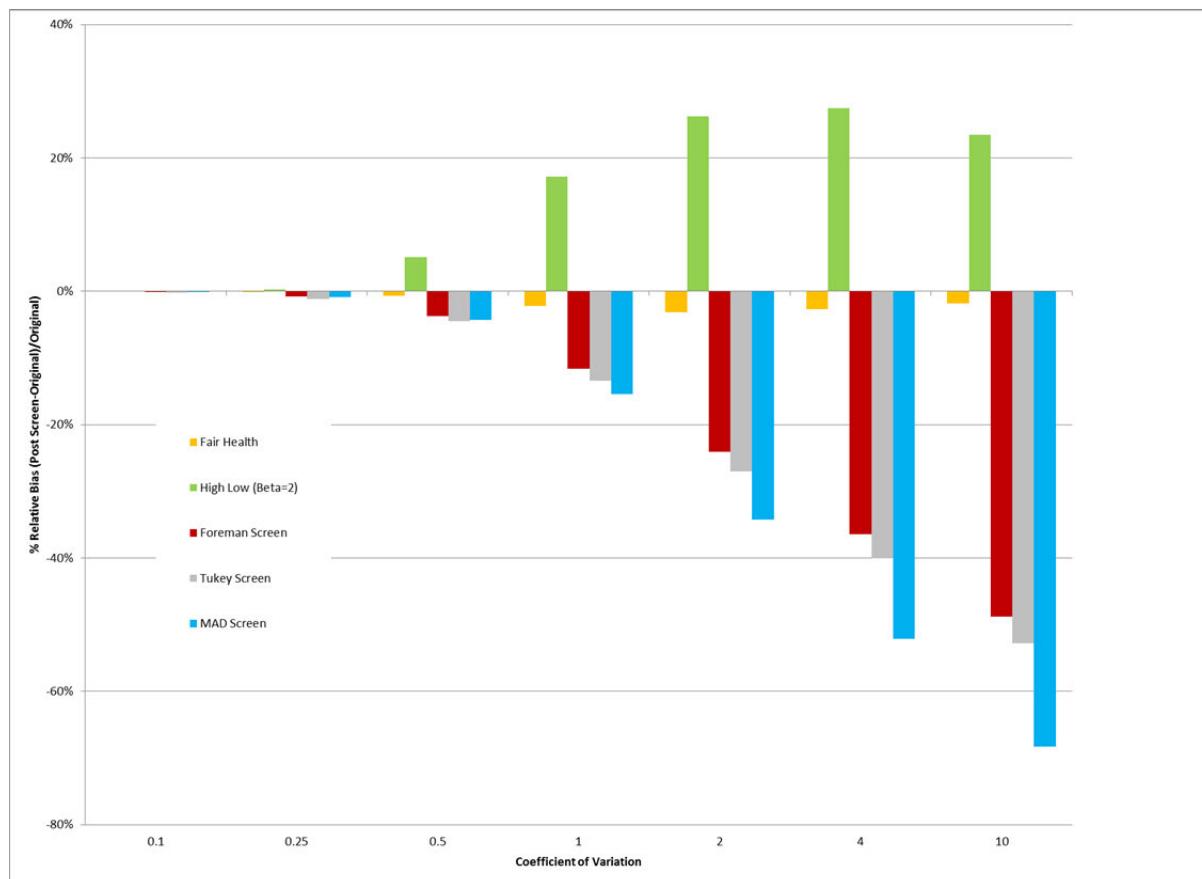
⁵⁷ See FAIR Health, "Extreme Outlier Methodology Changes Implemented in Products," available at http://www.fairhealthus.org/sites/fairhealthus.org/files/MAD%20Algorithm%20Communication_0.pdf (last visited Oct. 18, 2011) ("MAD Methodology").

⁵⁸ See MAD Methodology.

subject distribution of billed charges. Additionally, my simulation revealed that generally the Tukey and Foreman screens can only reduce the 80th percentile value.⁵⁹

88. I have added the FAIR Health outlier screen (four standard deviations) and MAD methodologies to my simulation. Figure 7 shows that, like the Tukey and Foreman screens, the FAIR Health screens generally reduces the 80th percentile value. Billed charge data have distributions truncated at zero and typically are right-skewed. With higher variation as indicated by the increasing coefficient of variation in the figure, the low screen cut-off point often falls below the lowest values in the distribution. As a result, few or no low values are removed by the screen. A MAD screen will likely result in a negative lower bound cut-off point, removing no low values from the billed charge distribution while it continues to remove high values from the distribution at the upper bound. A MAD screen trims the upper bound only, resulting in a substantial reduction in the 80th percentile value for highly variable data when compared to the pre-screen data.

Figure 7: Outlier Screen Simulation, $\beta = 2$, at the 80th Percentile



89. The FAIR Health method reduces the 80th percentile value for some assumptions about variation more than the Tukey or Foreman screens. These simulations indicate that it will not result in an increased value as is possible with the high-low screen. Importantly,

⁵⁹ See Cantor Responsive Merits Report at ¶¶ 138-151 and Appendix D.

FAIR Health has decided to manage outliers with an automated screen. In contrast, Dr. Foreman has compiled his data with no management of outliers. The FAIR Health approach is consistent with standard industry practices related to large database management. Dr. Foreman's approach is not. As a reflection of what would be chosen in the world but for the challenged conduct, the FAIR Health screen indicates that Dr. Foreman's unscreened proffered benchmarks contain percentile values that are inappropriate for the analysis of the alleged bias.

2. Comparisons with PHCS

90. Ingenix released PHCS data for 2010. The last release of the 2010 PHCS dental data was in July after which PHCS was replaced by the FH Dental Module. I have conducted analysis comparing the first release of the FAIR Health data with the last release of the PHCS data.
91. Importantly, there is a potential gap in the vintage of the PHCS data relative to the FAIR Health information. I understand that twelve-month average PHCS 2010_2 data were released in July of 2010. In contrast, the FAIR Health data were collected from January 2010 to January 2011. PHCS values are potentially lagged by 6 months relative to the FAIR Health values. To investigate what effect this lag might have on the results, I adjusted the PHCS percentile values for the time difference in billed charges.⁶⁰
92. The time adjustment to PHCS values indicates small variations in the measured percent differences. As shown in Table 22, both the Foreman and the Scientific Literature metrics indicate claim-weighted results that are less than one percent for the overall dataset and for the subset of claims of more than 40 claims. Overall, these data suggest that when adjusted for the time differences, there is no appreciable downward bias in the PHCS data compared to the FAIR Health data. These results also are consistent with the 2 percent claim-weighted result that I found comparing 2006 PHCS to 2006 NDAS data.⁶¹

⁶⁰ I have used the BLS CPI for dental services for the time adjustment. In the analysis of medical and surgical procedures below, I use the BLS CPI for physicians' services. This standard approach results in a smaller time adjustment than what would be indicated by using Dr. Foreman's 0.5 percent per month estimate. See Foreman Declaration at ¶ 224.

⁶¹ See Cantor Class Certification Report at Table 16 and using the definition of the Scientific Literature Metric.

**Table 22: FAIR Health 2011 Dental Comparison with PHCS 2010 R2 Dental,
Time-Adjusted Percent Differences**

Comparison ⁵	Match/Weighting	Time-Adjusted Overall Percent Differences		
		Foreman Metric ¹	Scientific Literature Metric ²	Average Metric ³
FAIR Health 2011 v. PHCS 2010 R2 Dental⁴ (All data)	Simple	1.8%	-0.3%	0.8%
	PHCS 2010 R2 Claim-wtd.	0.8%	0.6%	0.7%
	PHCS 2010 R2 Revenue-wtd.	0.5%	0.3%	0.4%
	PHCS 2010 R2 Price-wtd.	0.6%	-1.0%	0.1%
FAIR Health 2011 v. PHCS 2010 R2 Dental⁴ (Claims>40)	Simple	2.1%	0.5%	1.2%
	PHCS 2010 R2 Claim-wtd.	0.7%	0.6%	0.7%
	PHCS 2010 R2 Revenue-wtd.	0.5%	0.3%	0.4%
	PHCS 2010 R2 Price-wtd.	0.9%	0.0%	0.4%
FAIR Health 2011 v. PHCS 2010 R2 Dental⁴ (Claims<40)	Simple	1.7%	-0.5%	0.7%
	PHCS 2010 R2 Claim-wtd.	3.7%	-0.6%	1.3%
	PHCS 2010 R2 Revenue-wtd.	1.2%	-2.0%	-0.3%
	PHCS 2010 R2 Price-wtd.	0.5%	-1.1%	0.1%
2010 - 2011 Inflation (PHCS)⁴:		1.4%		
Notes:				
1. Foreman Metric is based on Expert Report of Dr. Foreman and calculated as: (FAIR Health - PHCS)/PHCS.				
2. Scientific Literature Metric is calculated as: (FAIR Health - PHCS)/Fair Health.				
3. Average Metric is calculated as: (FAIR Health - PHCS)/((FAIR Health+PHCS)/2).				
4. PHCS 2010 R2 Dental data range: Jul 2009 - Jul 2010; FAIR Health data range Jan 2010 - Jan 2011. Time-adjustment calculated as percentage difference between average monthly BLS CPI for Dental Services for FAIR Health data range and PHCS 2010 R2 (399.176 - 393.739)/393.739.				
5. All comparisons exclude FAIR Heath records where mean value is greater than 80th percentile.				

93. Similarly, I have compared the 2010 PHCS values to the FAIR Health medical and surgical data. Again, the dates of the compared datasets require that I make an adjustment for time differences. Table 24 shows that for the empirical and overall comparisons, the time-adjusted claim weighted results differ on average by less than two percent using either the Scientific Literature or Average Metric. Again, these results corroborate my earlier findings with the commercial and government benchmarks.

Table 23: FAIR Health 2011 Medical/Surgical Comparison with PHCS 2010 R2 Medical/Surgical, Time-Adjusted Percent Differences

Comparison ⁶	Match/Weighting	Time-Adjusted Overall Percent Differences		
		Foreman Metric ¹	Scientific Literature Metric ²	Average Metric ³
FAIR Health 2011 v. PHCS 2010 R2 Medical/Surgical⁴ (All data)	Simple	1.9%	-1.8%	0.0%
	PHCS 2010 R2 Claim-wtd.	5.5%	0.3%	1.1%
	PHCS 2010 R2 Revenue-wtd.	1.1%	-0.5%	0.2%
	PHCS 2010 R2 Price-wtd.	-0.4%	-2.9%	-1.3%
FAIR Health 2011 v. PHCS 2010 R2 Medical/Surgical⁴ (Claims>40)	Simple	4.8%	-3.9%	0.6%
	PHCS 2010 R2 Claim-wtd.	5.3%	0.4%	1.1%
	PHCS 2010 R2 Revenue-wtd.	0.8%	-0.2%	0.2%
	PHCS 2010 R2 Price-wtd.	1.1%	-6.8%	-1.2%
FAIR Health 2011 v. PHCS 2010 R2 Medical/Surgical⁴ (Claims<40)	Simple	1.6%	-1.6%	0.0%
	PHCS 2010 R2 Claim-wtd.	17.7%	-2.0%	2.8%
	PHCS 2010 R2 Revenue-wtd.	4.0%	-4.2%	0.0%
	PHCS 2010 R2 Price-wtd.	-0.4%	-2.9%	-1.3%
2010 - 2011 Inflation (PHCS)⁵:		1.5%		
Notes:				
1. Foreman Metric is based on Expert Report of Dr. Foreman and calculated as: (FAIR Health - PHCS)/PHCS.				
2. Scientific Literature Metric is calculated as: (FAIR Health - PHCS)/Fair Health.				
3. Average Metric is calculated as: (FAIR Health - PHCS)/((FAIR Health + PHCS)/2).				
4. PHCS 2010 R2 Medical/Surgical data range: Nov 2009 - Nov 2010; FAIR Health data range May 2010 - May 2011.				
5. Time-adjustment calculated as percentage difference between average monthly BLS CPI for Physicians' Services for FAIR Health data range and PHCS 2010 R2 (334.876 - 329.924)/329.924.				
6. All comparisons exclude FAIR Heath records where mean value is greater than 80th percentile.				

94. The results above are further supported by statements from FAIR Health based on its own comparisons to the Ingenix data:

Does FAIR Health's new database produce different results than the previous database?

The UHRN's testing of the adjusted calculations across all these different procedures and services showed varied results. Sometimes the results calculated using the UHRN methodology were higher than those calculated using Ingenix's methods, other times they were lower, and sometimes they were the same. But generally the UHRN believes that applying the new methodology can enhance the completeness of the data and the transparency of its development.⁶²

My analysis of the FAIR Health data is consistent with FAIR Health's assessment. In combination with my other analysis of the commercial and government databases, there is no support for Plaintiffs' claim that PHCS values are systematically biased downward.

⁶² See FAIR Health, "F.A.Q." available at <http://www.fairhealthus.org/consumer-education/faq> (last visited Jul. 5, 2011).

G. Conclusions

95. Based on my review of the Foreman Declaration and my additional analyses of the newly produced data and issues raised by Dr. Foreman, I have reached the following conclusions:

- Using but not adopting the 5000 CPT Study data, Dr. Foreman and I reach completely opposite inferences about the alleged downward bias. This is due to the choice of whether the proffered benchmark or PHCS value is used in the denominator of the percent difference metric and the presence of questionable data values in the Foreman benchmarks. Dr. Foreman's Metric departs from the conventional formula to measure systematic bias and he uses the PHCS value challenged by Plaintiffs in the denominator. Using a metric that averages the benchmark and PHCS values fails to support Dr. Foreman's claim-weighted bias results even when using the questionable 5000 CPT Study data;
- Percentile values from derived and small-count CPT/geozip combinations are not random. They exhibit strong correlations with the commercial and government benchmark data and with 5000 CPT Study data compiled by Dr. Foreman. These data should not be excluded from consideration in the analysis of the alleged downward bias in this matter;
- Dr. Foreman's newest datasets continue to exhibit data compilation errors that are so severe they render his data unusable as reliable benchmarks for the values but for the challenged conduct;
- Using recently released FAIR Health dental and medical and surgical data as a benchmark for time-adjusted PHCS data demonstrates that PHCS values differ immaterially. These results provide further support for my earlier conclusions that when compared to an independent benchmark, PHCS values exhibit no material downward bias on average or across the board.



Robin Cantor

October 26, 2011

APPENDIX: Properties of Percent Difference Metrics

Let the two values drawn from the same distribution be called “B” and “I” and define three metrics designed to express the relative difference between these two values as (a) $\frac{B-I}{B}$, (b) $\frac{B-I}{I}$, and (c) $\frac{B-I}{(B+I)/2}$. One is interested in investigating the behavior of these three metrics by simulating their sampling distributions using data from hypothetical and empirical populations for the values and by approximating the expected values of these metrics.

Expected Value Derivation

Typically, means and variances of functions of random variables do not have simple closed form expressions, but can be approximated using the Taylor series expansion method,¹ provided that the density function is differentiable and has finite variance. Using the Taylor series expansion method, a general expression to approximate the expected value (or first moment) of the ratio of two random variables U and V can be written as: $E\left[\frac{U}{V}\right] \approx \frac{E[U]}{E[V]} - \frac{\text{cov}[U,V]}{E[V]^2} + \frac{E[U]}{E[V]^3} \text{var}[V]$.

Since the three metrics are in the form of ratios, we can apply this general expression to approximate the expected values. To test the properties of these metrics using random values drawn from the same distribution, we let U = B-I and V = B or I or (B+I)/2 depending on the metric of interest. In our particular case, the numerator is (B-I) and if B and I are independent and identically distributed (IID), the expected value of the numerator of these metrics is zero (i.e., $E[B - I] = 0$). In that case, the Taylor series approximation of the ratio estimator can be simplified to: $E\left[\frac{U}{V}\right] \approx -\frac{\text{cov}[U,V]}{E[V]^2}$ because the first and third terms in the equation above are zero.

The covariance between two random variables U and V is defined as

$$\text{cov}(U,V) = E[UV] - E[U]E[V].$$

¹ Abramowitz, M. and Stegun, I. A. (Eds.). Handbook of Mathematical Functions with Formulas, Graphs, and Mathematical Tables, 10th printing. New York: Dover, 1972.

Expected Value of Three Metrics

Metric: $\frac{B-I}{B}$

Based on the Taylor series expansion, the approximate expected value of the ratio is $\approx -\frac{\text{Cov}(B-I, B)}{E[B]^2}$. The numerator can be written as: $\text{Cov}(B - I, B) = E[(B - I)B] - E(B - I)E(B)$. Because the expected value of their differences is 0 (*i.e.*, $E(B - I) = 0$), the covariance is reduced to: $\text{Cov}(B - I, B) = E[(B - I)B] = E(B^2) - E(B * I) = E(B^2) - E(B)E(I)$. Since B and I are IID random variables, $E(B) = E(I)$,

$$\text{Cov}(B - I, B) = E(B^2) - [E(B)]^2 = \text{Var}(B).$$

Thus, the expected value of this metric is $\approx -\frac{\text{Cov}(B-I, B)}{E[B]^2} = -\frac{\text{Var}(B)}{E[B]^2}$. Since variance and the squared expected value are never negative, the expected value of the metric $\frac{B-I}{B}$ must be a negative quantity.

Metric: $\frac{B-I}{I}$

Based on the Taylor series expansion, the approximate expected value of the ratio is $\approx -\frac{\text{Cov}(B-I, I)}{E[I]^2}$. The numerator can be written as: $\text{Cov}(B - I, I) = E[(B - I)I] - E(B - I)E(I)$. Again because the expected value of their differences is 0, the covariance is reduced to: $\text{Cov}(B - I, I) = E[(B - I)I] = -E(I^2) + E(B * I) = -E(I^2) + E(B)E(I)$. Since B and I are IID random variables, $E(B) = E(I)$, $\text{Cov}(B - I, I) = -(E(I^2) - [E(I)]^2) = -\text{Var}(I)$

Thus, the expected value of this metric $\left[\frac{B-I}{I}\right] \approx -\frac{\text{Cov}(B-I, I)}{E[I]^2} = +\frac{\text{Var}(I)}{E[I]^2}$ and this must be a positive quantity.

Metric: $\frac{B-I}{(B+I)/2}$

Based on the Taylor series expansion, the approximate expected value of this metric is

$$E\left[\frac{B-I}{(B+I)/2}\right] \approx -\frac{\text{Cov}(B-I, (B+I)/2)}{E[(B+I)/2]^2}.$$

A general expression for covariance of simple combinations of random variables is:

$$\text{Cov}(aX + bY, cW + dV) = ac\text{Cov}(X, W) + ad\text{Cov}(X, V) + bc\text{Cov}(Y, W) + bd\text{Cov}(Y, V)$$

Where X, Y, W, V are generic symbols for random variables and a, b, c, d are numerical constants. Applying this general expression to the covariance in this metric, we can substitute: ($a=1, X=B$), ($b=-1, Y=I$), ($c=\frac{1}{2}, W=B$), and ($d=\frac{1}{2}, V=I$), which yields

$$\text{Cov}(B - I, \frac{1}{2}B + \frac{1}{2}I) = \frac{1}{2}\text{Cov}(B, B) + \frac{1}{2}\text{Cov}(B, I) - \frac{1}{2}\text{Cov}(I, B) - \frac{1}{2}\text{Cov}(I, I)$$

The middle two terms cancel each other and the covariance in the numerator is simply reduced to $\frac{1}{2}\text{Cov}(B, B) - \frac{1}{2}\text{Cov}(I, I) = \frac{1}{2}\text{Var}(B) - \frac{1}{2}\text{Var}(I) = 0$ because the two random variables B and I came from the same distribution having the same variance. Thus, the expected value of this metric is 0.

Hypothetical Data Analysis

Pairs of values were randomly drawn from the same hypothetical but known distributions to represent implementation of the “B” and “I” values above. The relative difference metrics were calculated for each pair, and this process was repeated 100,000 times. If the sampled value was negative, sampling was repeated until a positive value was selected. The average values of these three metrics were calculated. Table A.1 shows the results of random draws from a normal distribution; Table A.2 shows the results of random draws from a log-normal distribution. By definition, the coefficient of variation is the standard deviation divided by the mean. Since the means are 10 fold increases, the standard deviation also increases by a factor of 10, thus resulting in the same expected values.

Table A.1: Simulated and Expected Values for Three Metrics using Various Means and Standard Deviations Drawn from a Normal Distribution

Mean	SD	(B-I)/B		(B-I)/I		(B-I)/(1/2(B+I))	
		Simulation	Expected Value	Simulation	Expected Value	Simulation	Expected Value
100	5	-0.22%	-0.25%	0.28%	0.25%	0.03%	0.00%
100	10	-1.04%	-1.00%	1.03%	1.00%	0.00%	0.00%
100	20	-4.71%	-4.00%	4.60%	4.00%	-0.05%	0.00%
100	30	-18.73%	-9.00%	14.83%	9.00%	-0.07%	0.00%
100	50	-145.87%	-25.00%	120.01%	25.00%	-0.23%	0.00%
1000	50	-0.25%	-0.25%	0.26%	0.25%	0.00%	0.00%
1000	100	-0.96%	-1.00%	1.10%	1.00%	0.07%	0.00%
1000	200	-4.63%	-4.00%	4.55%	4.00%	-0.05%	0.00%
1000	300	-14.51%	-9.00%	18.96%	9.00%	0.12%	0.00%
1000	500	-151.96%	-25.00%	997.67%	25.00%	-0.21%	0.00%
10000	500	-0.26%	-0.25%	0.24%	0.25%	-0.01%	0.00%
10000	1000	-0.95%	-1.00%	1.11%	1.00%	0.08%	0.00%
10000	2000	-4.63%	-4.00%	4.65%	4.00%	0.01%	0.00%
10000	3000	-15.12%	-9.00%	33.36%	9.00%	0.05%	0.00%
10000	5000	-240.00%	-25.00%	112.46%	25.00%	0.05%	0.00%

Table A.2: Simulated and Expected Values for Three Metrics using Various Means and Standard Deviations Drawn from a Log Normal Distribution

Mean	SD	(B-I)/B		(B-I)/I		(B-I)/(1/2(B+I))	
		Simulation	Expected Value	Simulation	Expected Value	Simulation	Expected Value
100	30	-9.16%	-9.00%	8.82%	9.00%	-0.15%	0.00%
100	50	-24.96%	-25.00%	24.80%	25.00%	-0.09%	0.00%
100	80	-64.47%	-64.00%	63.64%	64.00%	0.02%	0.00%
100	100	-99.15%	-100.00%	98.42%	100.00%	-0.34%	0.00%
100	120	-144.18%	-144.00%	144.03%	144.00%	0.24%	0.00%
1000	300	-8.86%	-9.00%	9.18%	9.00%	0.17%	0.00%
1000	500	-25.21%	-25.00%	25.35%	25.00%	0.07%	0.00%
1000	800	-62.22%	-64.00%	64.26%	64.00%	0.60%	0.00%
1000	1000	-99.74%	-100.00%	100.41%	100.00%	0.21%	0.00%
1000	1200	-144.67%	-144.00%	143.33%	144.00%	0.25%	0.00%
10000	3000	-8.70%	-9.00%	9.21%	9.00%	0.25%	0.00%
10000	5000	-24.37%	-25.00%	25.40%	25.00%	0.31%	0.00%
10000	8000	-63.84%	-64.00%	63.72%	64.00%	0.05%	0.00%
10000	10000	-100.15%	-100.00%	101.52%	100.00%	0.23%	0.00%
10000	12000	-142.68%	-144.00%	143.07%	144.00%	0.23%	0.00%

Empirical Data Analysis

In this testing of the metrics using actual Foreman or PHCS data, we examined three groups of CPT/geozip combinations, derived from the 300, 500, and 5,000 studies as determined by Dr. Foreman. For each CPT/geozip combination, the 80th percentile value is extracted and a random perturbation is added onto the original 80th percentile value to arrive at a random replication of the original 80th percentile value. The perturbation is based on a random draw from a normal distribution with mean zero and an estimated standard deviation from the set of claims for that particular CPT/geozip combination based on the percentile distribution. Sampling was repeated until the randomly perturbed 80th percentile value is positive. Differences between the original and the randomly perturbed 80th percentile value are measured by the three different metrics. The original and the randomly perturbed values can be thought of as examples of the “B” and “I” metric and the expected value derivation shown. The random deviation was applied to the contributor benchmark data provided by Dr. Foreman and also to PHCS data in the Foreman footprint.

The sampling was repeated 100 times for each footprint. The average of each metric was calculated for each simulation, thus there were 100 average $(B - I)/B$, 100 average $(B - I)/I$, and 100 average $(B - I)/\frac{1}{2}(B + I)$. Table A.3 displays the minimum, mean and maximum of the averages of the 100 simulations for each footprint using the Foreman benchmark data; Table

A.4 shows the summary information using PHCS 2007 R2 data in the Foreman footprint. The claim weighted values are based on the population weighted claim count for PHCS.

Table A.3: Minimum, Mean and Maximum Values for Three Metrics using Foreman Contributor Data across 100 Simulations

Footprint	Match	CPT/Geozip Count	(B-I)/B			(B-I)/I			(B-I)/(1/2(B+I))		
			Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
300	Simple	63,812	-7.00%	-5.60%	-4.20%	19.40%	43.10%	474.50%	2.70%	3.00%	3.30%
500	Simple	161,475	-7.00%	-6.10%	-5.30%	25.10%	52.00%	416.60%	2.40%	2.60%	2.70%
5000	Simple	436,805	-6.00%	-5.20%	-4.60%	35.80%	64.10%	374.40%	2.30%	2.40%	2.50%
300	Claim Weighted	63,812	-1.70%	-0.70%	0.40%	11.60%	22.80%	87.40%	1.70%	2.80%	3.90%
500	Claim Weighted	161,475	-1.70%	-1.00%	0.20%	14.60%	29.90%	181.90%	1.90%	2.70%	4.20%
5000	Claim Weighted	436,805	-3.30%	-2.30%	-1.30%	22.70%	39.20%	195.50%	2.00%	2.90%	3.90%

Table A.4: Minimum, Mean and Maximum Values for Three Metrics using PHCS 2007 R2 Data in the Foreman Footprint across 100 Simulations

Footprint	Match	CPT/Geozip Count	(B-I)/B			(B-I)/I			(B-I)/(1/2(B+I))		
			Min	Mean	Max	Min	Mean	Max	Min	Mean	Max
300	Simple	63,577	-1.00%	-0.70%	-0.50%	13.90%	25.20%	249.00%	2.40%	2.70%	2.90%
500	Simple	161,101	-1.00%	-0.90%	-0.80%	18.00%	33.00%	343.90%	2.40%	2.60%	2.70%
5000	Simple	390,442	-1.10%	-1.00%	-0.90%	20.80%	56.20%	1050.00%	2.30%	2.40%	2.50%
300	Claim Weighted	63,577	-1.40%	-0.50%	0.50%	10.00%	19.80%	198.00%	1.60%	2.60%	3.80%
500	Claim Weighted	161,101	-1.60%	-0.60%	0.20%	10.40%	25.10%	429.90%	1.60%	2.60%	3.50%
5000	Claim Weighted	390,442	-1.40%	-0.60%	0.20%	12.10%	35.70%	1225.30%	1.80%	2.60%	3.40%



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Attachment 1: Cantor CV

Robin A. Cantor, Ph.D. Principal

Professional Profile

Dr. Robin Ann Cantor is a Principal in Exponent's Alexandria, VA office. She specializes in applied economics, environmental and energy economics, statistics, risk management, and insurance claims analysis. Prior to joining Exponent, she led the Liability Estimation practice at Navigant Consulting and assisted companies and financial institutions with analysis to better understand asbestos and other product liability exposures. Other positions she has held include: Principal and Managing Director of the Environmental and Insurance Claims Practice at LECG, LLC, Program Director for Decision, Risk, and Management Sciences, a research program of the National Science Foundation, and senior research appointments at Oak Ridge National Laboratory. Dr. Cantor has a faculty appointment in the Graduate Part-time Program in Engineering of the Johns Hopkins University. She was the President of the Society for Risk Analysis in 2002, and from 2001-2003, she served as an appointed member of the Research Strategies Advisory Committee of the US Environmental Protection Agency's Science Advisory Board. She is a member of the Executive Committee for the Women's Council on Energy and the Environment. Dr. Cantor's testimonial experience includes analysis of economic damages, product liability estimation in bankruptcy matters and insurance disputes, statistical analysis of asbestos settlements, analysis of premises and product claims, cost contribution allocation in Superfund disputes, analysis of derailment risks, reliability of statistical models and estimation methods, and economic analysis of class certification issues. She has prepared expert reports that address economic issues in antitrust, commercial practices and contracts, intellectual property, employment discrimination, false advertising, regulation, and other areas of product and market analysis. Dr. Cantor has submitted analysis, testimony and affidavits in federal arbitration, regulatory and Congressional proceedings, and state and federal courts. Dr. Cantor's publications include refereed journal articles, book chapters, expert reports, reports for federal sponsors, and a book on economic exchange under alternative institutional and resource conditions.

Academic Credentials and Professional Honors

Ph.D., Economics, Duke University, 1985
B.S., Mathematics, Indiana University of Pennsylvania, 1978

Fellow, Society for Risk Analysis, 2002
President, Society for Risk Analysis, 2002
YWCA Tribute to Women Award for Business and Industry, 1990

Society for Risk Analysis Presidential Recognition Award, 2008; Society for Risk Analysis Outstanding Service Award, 1999; NSF Director's Award for Superior Accomplishment, 1996; NSF Special Act Award, 1995; NSF Director's Award for Program Officer Excellence, 1994;

Oak Ridge National Laboratory Significant R&D Accomplishment Award, 1993; Martin Marietta Special Achievement Award, 1990; Martin Marietta Special Achievement Award, 1989; Martin Marietta Energy Systems Significant Event Award, 1988; C.B. Hoover Scholar, 1980–1981; Mellon Fellowship, 1978–1981

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The U.S.-EC Fuel Cycle Study: Background Document to the Approach and Issues. Oak Ridge National Laboratory, ORNL/TM-2500, November, 1992 (with L. W. Barnhouse, D. Burtraw (Resources for the Future), G. F. Cada, C. E. Easterly, A. M. Freeman (Bowdoin College), W. Harrington (Resources for the Future), T.D. Jones, R. L. Kroodsma, A. J. Krupnick (Resources for the Future), R. Lee, H. Smith (DOE), A. Schaffhauser, and R. S. Turner).

What are the Problems of Equity and Legitimacy Facing a Management Strategy for the Global Commons? Managing the Global Commons: Decision Making and Conflict Resolution in Response to Climate Change, Oak Ridge National Laboratory, ORNL/TM-11619, July, 1990 (with Roger Kasperson in Steve Rayner, Wolfgang Naegeli, and Patricia Lund).

Markets, Distribution, and Exchange after Societal Cataclysm, Oak Ridge National Laboratory, ORNL-6384, November 1989 (with S. Rayner and S. Henry).

Information. Chapter 5 of A Compendium of Options for Government Policy to Encourage Private Sector Responses to Potential Climate Change, DOE/EH-0102, Report to Congress, October, 1989 (with G. G. Stevenson and P. J. Sullivan).

Agriculture and Forestry. Chapter 10 of A Compendium of Options for Government Policy to Encourage Private Sector Responses to Potential Climate Change, DOE/EH-0102, Report to Congress, October, 1989 (with W. Naegeli and A. F. Turhollow, Jr.).

Evaluation of Implementation, Enforcement and Compliance Issues of the Bonneville Model Conservation Standards Program, Vol. I and II, ORNL/CON-263, July 1989 (with Steve Cohn).

Gas Furnace Purchases: A Study of Consumer Decision Making and Conservation Investments. ORNL/TM-10727, October 1988 (with David Trumble).

An Analysis of Nuclear Power Plant Construction Costs. DOE/EIA-0485, 1986 (with J. G. Hewlett and C. G. Rizy).

Nuclear Reactor Decommissioning: A Review of the Regulatory Environments. ORNL/TM-9638, 1986.

Nuclear Power Options Viability Study, Vol. I, Executive Summary, ORNL/TM-9780/1, 1986 (with D. B. Trauger et al.).

Nuclear Power Options Viability Study, Vol III, Nuclear Discipline Topics. ORNL/TM-9780/3, 1986 (with D. B. Trauger et al.).

Clinch River Breeder Reactor: An Assessment of Need for Power and Regulatory Issues, ORNL/TM-8892, September 1983 (with D. M. Hamblin et al.).

Selected Presentations

Cantor RA. Evaluating vulnerabilities and identifying emerging risks. Invited presentation, The Conference Board EHS Legal Counsel Meeting, Houston TX, January 15–16, 2009.

Cantor RA. Using exposure science to ascertain asbestos liabilities. Invited CLE presentation, Business Valuation Resources, LLC Teleconference, November 18, 2008.

Cantor RA. Weather and temperature: Emerging health issues for US companies. REBEX 2008, Wheeling IL, October 23–24, 2008.

Cantor RA. Asbestos risk transfers: Unlocking value by walling off asbestos liabilities. Invited CLE session at Willkie Farr & Gallagher, New York, NY, June 4, 2008.

Cantor RA. The future of asbestos—New techniques for unlocking value by selling liabilities to investors. Mealey's™ Teleconference, March 25, 2008.

Cantor RA. Update on other U.S. long-tailed product liabilities. Invited presentation, 4th International Asbestos Claims & Liabilities Conference: The Practical Guide to Litigating, Settling and Managing Asbestos Claims, London, January 30–31, 2008.

Cantor RA. Tax or cap: What are the real differences for carbon policy in the US? Invited session and presentation, McDermott Will & Emery 10th Annual Energy Conference, Washington DC, October 9–10, 2007.

Cantor RA. Managing nanotechnology's life cycle risks responsibly. Invited ALI-ABA teleconference, June 27, 2007.

Cantor RA. Carbon emissions—Planning for the change. Invited teleconference, Environmental Law Network, June 15, 2007.

Cantor RA. Liability estimation and the historical future. Invited presentation, Mealey's™ Asbestos Bankruptcy Conference, Chicago, IL, June 7–8, 2007.

Cantor RA. Renewables and the value proposition for carbon credits. Invited presentation, McDermott Will & Emery 9th Annual Energy Conference, Washington DC, October 19–20, 2006.

Cantor RA. The ABCs of the value proposition for carbon credits. Invited presentation, the Environmental Trading Congress, New York, NY, July 24–25, 2006.

Cantor RA, Lyman M. Liability estimation in U.S. bankruptcy cases. London Underwriting Centre, London, UK, January 10, 2006.

Cantor RA, Lyman M. The status of the FAIR Act. London Underwriting Centre, London, UK, January 10, 2006.

Cantor RA. Economic appraisal of ecological assets. Invited presentation, U.S. Environmental Protection Agency Science Advisory Board “Science and the Human Side of Environmental Protection” Series, Washington, DC, July 6, 2002.

Cantor RA. Scientists and Homeland Security—The relevance of risk analysis. Invited presentation, Council of Scientific Society Presidents, Washington, DC, May 2002.

Cantor RA. NRD rules and economics. Invited presentation, Environmental and Admiralty Law Committees of the Association of the Bar of the City of New York, December 7, 2000.

Cantor RA. Revealed preferences and environmental risks: Lessons learned from two policy debates. Annual Meetings of the Society For Risk Analysis, Phoenix, AZ, December 8, 1998.

Cantor RA. Valuing environmental impacts: Lessons learned from the natural resource damage debate. Invited Paper, Society of Environmental Toxicology and Chemistry, 19th Annual Meeting, November 19, 1998.

Cantor RA. How will climate change affect economics and politics? Invited panel speaker, Policy and Politics of Climate Change, ABA Section of Natural Resources, Energy, and Environmental Law Fall Meeting, October 8, 1998.

Cantor RA. Natural resource damage rules: A search for the path of least resistance in value disputes? George Washington University Seminar Series on Environmental Values and Strategies, September 1997.

Cantor RA. Rethinking the science of risk management: Changing paradigms of the process and function. Operations and Information Management Department Workshop, Wharton School of the University of Pennsylvania, November 1995.

Cantor RA, Arkes H. Interdisciplinary perspectives on experimental methods. 1995 Meetings of the American Economic Association, January 1995.

Cantor RA. Risk management: Four different views. Invited presentation, The Conservation of Great Plains Ecosystems Symposium, April 1993.

Cantor RA. Human dimensions of global change: A white paper on the USGCRP research programs. National Academy of Sciences Board on Global Change, November 1993.

Cantor RA, Rayner S. Changing perceptions of vulnerability. Invited paper, NCAR/UCAR Summer Institute on Industrial Ecology and Global Change, July 17–31, 1992.

Cantor RA. Should economic considerations limit the conservatism of risk assessment? Invited paper, Workshop of the International Society of Regulatory Toxicology and Pharmacology on Risk Assessment and OMB's Report on its Application in Regulatory Agencies, Washington, DC, June 11, 1991.

Cantor RA. Beyond the market: Recent regulatory responses to the externalities of energy production. Annual Meetings of the National Association of Environmental Professionals, Baltimore, MD, April 30, 1991.

Cantor RA. Understanding community preferences at Superfund sites. National Meeting of EPA Community Relations Coordinators, Chicago, IL, April 4–6, 1990.

Cantor RA. Methodological myths and modeling markets: A common framework for analyzing exchange. Second Annual International Conference on Socio-Economics, Washington, DC, March 1990.

Cantor RA, Schoepfle GM, Szarleta EJ. Sources and consequences of hypothetical bias in economic analyses of risk behavior. 1989 Meetings of Society for Risk Analysis, October 1989.

Cantor RA, Jones D, Lieby P, Rayner S. Policies to encourage private sector responses to potential climate change. 1989 Meetings of International Association of Energy Economists, October 1989.

Cantor RA, Szarleta EJ. The experimental approach in public policy analysis: precepts and possibilities. Public Choice Society and Economic Science Association Annual Meetings, Orlando, FL, March 17–19, 1989.

Cantor RA, Rayner S. Global disaster management: Developing principles for research. 1988 Meetings of the Association for Public Policy Analysis and Management, October 1988.

Cantor RA. Implementation and enforcement issues from early adopter experience. Regional Evaluation Network, Northwest Power Planning Council, Portland, OR, June 1988.

Cantor RA. Using information from toxic-tort litigation to value the health and safety consequences of regulatory decisions. Public Policy Workshop, the Department of Economics and Waste Management Research and Education Institute, University of Tennessee, Knoxville, TN, February 1988.

Cantor RA, Bishop R, Jr. Valuing safety and health effects in regulatory decisions: A revealed-preference approach. 1987 Annual Meeting of the Society for Risk Analysis, November 3, 1987.

Cantor RA. Government intervention and technology prices: The CANDU example. Invited paper, WATTEC Conference, Knoxville, TN, February 19, 1987.

Cantor RA. Fairness hypothesis and managing the risks of societal technology choices. 1986 Winter Annual Meeting of the American Society of Mechanical Engineers, Anaheim, CA, December 10–12, 1986.

Cantor RA. A retrospective analysis of technological risk: The case of nuclear power. Invited paper, Center of Resource and Environmental Policy Workshop Series, Vanderbilt University, Nashville, TN, December 4, 1986.

Cantor RA, Petrich C, Mercier J-R. Evaluation of a large-scale charcoal project in Madagascar: Attacking the deforestation problem from the supply side. 1986 IAEE North American Conference, Cambridge, MA, November 19–21, 1986.

Cantor RA, Rayner S. Tools for the job: Choosing appropriate strategies for risk management. 1986 Annual Meeting of the Society for Risk Analysis, Boston, MA, November 9–12, 1986.

Cantor RA, Rayner S. Thinking the unthinkable: Preparing for global disaster. 1986 Annual Meeting of the Society for Risk Analysis, Boston, MA, November 9–12, 1986.

Cantor RA, Rayner S, Braid B. The Role of liability preferences in societal technology choices: Results of a pilot study. 1985 Annual Meetings of Society for Risk Analysis, Washington, DC, October 8, 1985.

Conference Participation

Invited panelist for “An Integrated Risk Framework for Gigawatt-Scale Deployments of Renewable Energy: The Wind Energy Case Study,” 2009 Annual Meeting for the Society for Risk Analysis, Baltimore, MD, December 9, 2009.

Invited session organizer and panelist for “Global Warming and Greenhouse Gas Controls: What do they mean for you?” 2008 Annual Meeting of the National Association of Publicly Traded Partnerships, Washington DC, June 26, 2008.

Co-chair, “Second World Congress on Risk,” Guadalajara, Mexico, June 2008.

Invited panelist for “Climate Litigation: The Next Asbestos or the Next Y2K?” ABA Section of Litigation Annual Conference, Washington DC, April 17, 2008.

Invited panelist for “Business of Mitigation: Carbon Offsets and Trading,” Oxford University Capstone Conference, Oxford, UK, September 10, 2007.

Panelist for “Issues Concerning Implementation,” at the Public Forum on OMB’s Proposed Risk Assessment Bulletin: Implications for Practice Inside and Outside Government, sponsored by Society for Risk Analysis, Society of Environmental Toxicology and Chemistry in North America, Society of Toxicology, and International Society of Regulatory Toxicology and Pharmacology.

Session Chair, “Challenges Facing Industrial Countries,” with key-note speeches by Philippe Busquin, EU Commissioner for Research, and Dr. John Graham, Administrator of the US Office of Information and Regulatory Affairs, Inaugural Conference of the International Risk Governance Council, Geneva, Switzerland, June 29, 2004.

Co-Chair, “First World Congress on Risk,” Brussels, Belgium, June 2003.

Chair of the Organizing Committee, 2001 Annual Meetings for the Society for Risk Analysis.

Member of the Organizing Committee, Risk and Governance Symposium, Society for Risk Analysis, June 2000.

Organizing Committee Member for the 1996, 1997, 1998, and 2002 Annual Meetings of the Society for Risk Analysis.

Panelist for Net Environmental Benefits Assessment for Restoration Projects after Oil Spills, Conference on Restoration for Lost Human Uses of the Environment, Washington, DC, May 1997.

Session Organizer and Chair for Cost Benefit Analysis and Risk Assessment at the 1996 Annual Meeting of the Society for Risk Analysis.

Panelist for Challenges in Risk Assessment and Risk Management sponsored by The Annenberg Public Policy Center of the University of Pennsylvania at the National Press Club, Washington, DC, May 16, 1996.

Panelist for Media and Risk in a Democracy: Who Decides What Hazards Are Acceptable? At the 1995 Annual convention of the Association for Education in Journalism and Mass Communication.

Session Organizer and Co-Chair for Experimental Methods: Insights from Economics and Psychology at the 1995 Meetings of the American Economic Association.

U.S. Organizer for the Third Japan-U.S. Workshop on Global Change Modeling and Assessment: Improving Methodologies and Strategies, Hawaii, October 1994.

Cluster Organizer for three sessions on Competitiveness at the Fall Meeting of the Operations Research Society of America/The Institute of Management Sciences, 1994.

Roundtable Panelist for Risk Communication Research: Defining Practitioner Needs at the 1994 Meetings of the Society for Risk Analysis.

Workshop Organizer for Organizational Transformation and Quality Systems, National Science Foundation, 1993.

Session Chair and Organizer for the NSF/Private Sector Research Initiative Projects at the 1992 Meetings of the Society for Risk Analysis.

Roundtable Panelist for the EPA Session on Risk Communication at the 1990 Meetings of the Society for Risk Analysis.

Session Chair and Organizer for the Computer Assisted Market Institutions Session at the Advanced Computing for the Social Sciences Conference, April 1990.

Discussant for the Issues in LDC Public Finance Session at the 1988 Meetings of the American Economic Association.

Session Chair and Organizer for Social Science Innovations in Risk-Analysis Methods, Special Session at the 1988 Meetings of the Society for Risk Analysis.

Prior Experience

Managing Director, Navigant, 2004–2008

Lecturer, Graduate Program, Johns Hopkins University, Engineering and Applied Science Programs for Professionals, Program in Environmental Engineering, Science and Management, 1996–present

Principal and Managing Director, LECG, 1999–2004

Senior Managing Economist, LECG, 1999

Managing Economist, LECG, 1996–1998

Member, U.S. Environmental Protection Agency, Science Advisory Board, Research Strategies Advisory Committee, 2001–2003

Program Director, Decision, Risk, and Management Science, National Science Foundation, 1992–1996

Coordinator, NSF Human Dimensions of Global Change, 1992–1996

Project Manager, Oak Ridge National Laboratory, 1990–1991

Technical Assistant to the Associate Director, Advanced Energy Systems, Oak Ridge National Laboratory, 1989–1990

Group Leader, Social Choice and Risk Analysis Group, Energy and Economic Analysis Section, Oak Ridge National Laboratory, June 1987–1989

Research Staff, Energy and Economic Analysis Section, Oak Ridge National Laboratory, Oak Ridge National Laboratory, October 1982–1987

Consultant, Indonesian Energy Project, Harvard Institute For International Development, July 1987

Visiting instructor, North Carolina Central University, Spring 1982

Advisory and Other Appointments

- National Research Council Committee to Review the Department of Homeland Security's Approach to Risk Analysis, November, 2008–present
- Executive Committee, Women's Council on Energy and the Environment, 2006–present
- Board Member, Women's Council on Energy and the Environment, 2004–2006
- Member, Advisory Group for the Joint Global Change Research Institute, a collaboration between Pacific Northwest National Laboratory and the University of Maryland, 2004–2008
- Member, Planning Committee for a study to evaluate the U.S. National Assessment of the Potential Consequences of Climate Variability and Change, coordinated through Carnegie Mellon University, 2004
- Neutral technical panelist working with Arbitrator Anthony Sinicropi on negotiation issues related to the pilots' compensation contract. Retained by US Airways and the Air Line Pilots Association (ALPA), 2001 and 2002
- Advisory Board Member, Johns Hopkins University Graduate Part-Time Program in Environmental Engineering and Science, 2000–2004
- Planning Committee Member, Carnegie Council on Ethics and International Affairs Long Term Study of Culture, Social Welfare, and Environmental Values in the U.S., China, India, and Japan, initiated January 1997
- Vice-Chair, U.S. Global Change Research Program working group on Assessment Tools and Policy Sciences, 1994–1996
- US Federal Reviewer for the Intergovernmental Panel on Climate Change working group III 1995 Report on Socioeconomics
- NSF Principal for the Committee on the Environment and Natural Resources' Subcommittee on Risk Assessment, 1993–1996. Also served as the liaison between the Subcommittee on Risk Assessment and the Subcommittee on Social and Economic Sciences
- Advisory panel member for Environmental Ethics and Risk Management, National Academy of Public Administration and George Washington University, 1993–1994
- Science Advisory Board member for Consortium for International Earth Science Information Network, 1993
- Review Panel member for Economics and the Value of Information, NOAA, 1993
- NSF technical representative to the FCCSET Ad Hoc Working Group on Risk Assessment and member of its Subcommittee on Risk Assessment, 1992–1993
- NSF representative to Working Party of the FCCSET Subcommittee for Global Change Research on Assessment, 1992–1993
- Affirmative Action Representative for the Energy Division, Oak Ridge National Laboratory 1984–1989, AA Rep for the Central Management Organization of ORNL, October 1989 to November 1990
- Board of Directors, Vice President (1987–1988), President (1988–1989), Matrix Organization, The Business Center for Women and Minorities, Knoxville, TN

Editorships and Editorial Review Boards

- Editorial Board, *Journal of Risk Analysis*, 1997–present
- Editorial Board, *Journal of Risk Research*, 1997–2005

Peer Reviewer

- The Energy Journal, Climate Change, Contemporary Economic Policy, Growth and Change, Ecological Applications, Risk Analysis, Duke University Press, Princeton University Press, J. of Environmental Economics and Management, Resources and Energy, The Environmental Professional, Journal of Risk Research, National Science Foundation, National Oceanic and Atmospheric Administration, FORUM, U.S. Environmental Protection Agency

Professional Affiliations

- American Economic Association
- Women's Council on Energy and the Environment
- Society for Risk Analysis
 - President, Society for Risk Analysis, 2002
 - President-Elect, Society for Risk Analysis, 2001
 - Councilor, Society for Risk Analysis, 1996–1999
- American Bar Association

Deposition /Trial Testimony

Available on request



Exponent
1800 Diagonal Road
Suite 300
Alexandria, VA 22314

telephone 571-227-7200
facsimile 571-227-7299
www.exponent.com

Attachment 2: Cantor Testimony in Last Four Years

Robin A. Cantor, Ph.D. Principal

Class Plaintiffs v. American Express Company and American Express Travel Services Company, Inc.

Friedman Law Group LLP (Plaintiffs)
US District Court Southern District of New York (04 Civ. 05432 (GBD))

- Declaration (November, 2007)
- Deposition (November 27, 2007)
- Reply Declaration (March, 2008)

In the Matter of Dana Corporation, Debtors.

Jones Day (Debtor)
US Bankruptcy Court, Southern District of New York
• Trial Testimony (December 11, 2007)

In re Packaged Ice Antitrust Litigation

Spector, Roseman, Kodroff & Willis, P.C. (Class Plaintiffs)
US District Court Eastern District of Michigan
Case No. 2:08-md-01952 (PDB) MDL No. 1952
• Declaration (December, 2008)

The Howard Hughes Properties and Howard Hughes Corporation v. Kern River Gas Transmission Company

Bracewell & Giuliani LLP (Plaintiffs/Counterdefendants)
US District Court District of Nevada
Case No. 2:09-cv-00657-RLH-LRL
• Affidavit (October, 2009)
• Deposition (December, 2009)

TYR Sport Inc. v. Warnaco Swimwear Inc. dba Speedo USA

O'Neil LLP (Plaintiffs/Counterdefendants)

Case No. SACV 08-529-JVS(MLGx)

US District Court Central District of California

- Declaration (March 22, 2010)
- Declaration (April 5, 2010)
- Declaration (April 9, 2010)

In re Aetna UCR Litigation

Gibson, Dunn & Crutcher LLP (Defendants)

MDL No. 2020 Case No. 2:07-CV-3541

US District Court District of New Jersey

- Deposition (May 25, 2010)
- Deposition (December 17, 2010)

The Original Honeybaked Ham Company of the East, Inc. v. Allied Printing Company, Inc.

Law Offices of Brown and Black (Defendant)

Civil Action No. 009-843

Essex Superior Court, Commonwealth of Massachusetts

- Affidavit (December, 2010)
- Affidavit (April, 2011)
- Trial Testimony (October 11-12, 2011)

Public Hearing on MSHA's Proposed Rule: Lowering Miners' Exposure to Respirable Coal Mine Dust, Including Continuous Personal Dust Monitors (RIN 1219-AB64)

Murray Energy Corporation

Arlington, Virginia

- Public Testimony (February 15, 2011)

ATTACHMENT 3: MATERIALS CONSIDERED

I. MATERIALS INCORPORATED BY REFERENCE

The materials cited in the footnotes to the Cantor Class Certification Report dated Apr. 6, 2010, the Updated Responsive Class Certification Report of Dr. Robin Cantor dated May 21, 2010 and the Responsive Expert Report of Dr. Robin Cantor dated Nov. 10, 2010 in the instant matter and/or listed in Attachments 3, R2 and 3 thereto respectively are incorporated herein by reference.

II. LEGAL DOCUMENTS

A. Depositions

Deposition Transcript of Dr. Gordon Rausser (Dec. 6-7, 2010).
Deposition Transcript of Dr. Andrew Joskow (Dec. 10, 2010).
Deposition Transcript of Dr. Bernard Siskin (Dec. 14-15, 2010).
Deposition Transcript of Dr. Daniel Slottje (Dec. 16, 2010).
Deposition Transcript of Dr. Stephen Foreman (Oct. 11, 2011).
Deposition Transcript of Dr. Gordon Rausser (Oct. 12, 2011).

B. Expert Reports

Expert Report of Thomas R. McCarthy, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 10, 2010).
Responsive Expert Report of Monica G. Noether, Ph.D., Darlery Franco, et al. v. Connecticut General Life Insurance Co., et al. (filed Nov. 10, 2010).
Rebuttal Report of Dr. Daniel J. Slottje to the August 9, 2010 Expert Reports of Dr. Foreman and Dr. Siskin, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 10, 2010).
Responsive Expert Report of Dr. Andrew S. Joskow, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 10, 2010).
Responsive Expert Report of Bradford Cornell, Ph.D., Darlery Franco, et al. v. Connecticut General Life Insurance Co., et al. (filed Nov. 10, 2010).

C. Declarations

Declaration of Stephen Foreman, PhD, JD, MBA, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 24, 2010).
Declaration of Gordon Rausser, Ph.D., In Support of Reply Memorandum of Law in Further Support of Plaintiffs' Motion for Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 24, 2010).
Reply Declaration of Robert J. Axelrod in Further Support of Plaintiffs' Motion for Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 filed Nov. 24, 2010).

D. Other

Defendants' Opposition to Plaintiffs' Motion for Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 dated Nov. 15, 2010).

Reply Memorandum of Law in Further Support of Plaintiffs' Motion for Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 dated Nov. 24, 2010).

Memorandum In Support of Defendants' Motion to Strike Untimely Expert Reports and Improper Reply Materials or, in the Alternative, for an Opportunity to (1) Take Discovery on the Untimely Expert Reports, (2) Submit Responsive Expert Reports, and (3) Submit a Sur-Reply Brief in Opposition to Class Certification, In Re: Aetna UCR Litigation (MDL No. 2020 dated Feb. 14, 2011).

Plaintiffs' Memorandum of Law in Opposition to Defendants' Motion to Strike or, in the Alternative, for Leave to File a Sur-Reply, In Re: Aetna UCR Litigation (MDL No. 2020 filed Feb. 2, 2011).

III. BATES STAMPED DOCUMENTS

AET-C00103216

IV. DATASETS

A. FAIR Health

Data	File Name
Fair Health Dental	dacdc.dat
Fair Health Medical	macdc.dat
Fair Health Surgical	sacdc.dat

B. Ingenix Data

Data	File Name
2008-01 PHCS Dental ACDC	dacdc.dat
2008-07 PHCS Dental ACDC	dacdc.dat
2008-11 PHCS Medical ACDC	macdc.dat
2008-11 PHCS Surgical ACDC	sacdc.dat
2010-01 PHCS Dental ACDC	dacdc.dat
2010-05 PHCS Medical ACDC	macdc.dat
2010-05 PHCS Surgical ACDC	sacdc.dat
2010-07 PHCS Dental ACDC	dacdc.dat
2010-11 PHCS Medical ACDC	macdc.dat
2010-11 PHCS Surgical ACDC	sacdc.dat

C. Commercial & Government Benchmarks

Data	File Name
NDAS 2010	NDAS 2010 Pricing.xls
NDAS 2010	NDAS 2010 Geographic Multipliers.csv

V. PUBLICLY AVAILABLE INFORMATION

A. Websites

Centers for Medicare & Medicaid Services, “Prospective Payment Systems – General Information,” http://www.cms.gov/ProspMedicareFeeSvcPmtGen/01_overview.asp (last visited Mar. 25, 2011).

Camalier L, Eberly S, Miller J, Papp M. Environmental Protection Agency. Guideline on the Meaning and The Use of Precision and Bias Data Required by 40 CFR Part 58 Appendix A. EPA-454/B-07-001. January 2007, *available at* <http://www.epa.gov/ttnamti1/files/ambient/monitorstrat/precursor/07workshopmeaning.pdf> (last visited June 29, 2011).

Department of Ecology, State of Washington. Ecology Quality Assurance Glossary. *available at* http://www.ecy.wa.gov/programs/eap/qa/docs/QualityAssuranceGlossary_041410_final.pdf (last visited June 30, 3011).

Defense Logistics Agency. Environmental, Safety and Occupational Health Management System. I Am The Key. Policies and Procedures. Programmatic Sampling and Analysis Plan, *available at* https://www.dnsc.dla.mil/iamthekey/UploadedFiles/GENERAL_Policies&Guidelines_ps_ap_section_7_to_8.pdf (last visited June 29, 2011).

Environmental Protection Agency. Radon Glossary of Terms, *available at* www.epa.gov/radon/glossary.html (last visited June 29, 2011).

FAIR Health, “F.A.Q.” *available at* <http://www.fairhealthus.org/consumer-education/faq> (last visited Jul. 5, 2011).

FAIR Health, “Letter from FAIR Health’s President,” *available at* <http://www.icontact-archive.com/aaeAnbeTqkYZaFrqTeqAzwU5KAWVjMrV#successfullaunch> (last visited Jun. 20, 2011).

FAIR Health, “FH™ RV and FH Benchmarks Release Schedule,” *available at* http://fairhealthus.org/sites/fairhealthus.org/files/FAIR%20Health%20Product%20Release%20Schedule_0.pdf (last visited Jun. 20, 2011).

FAIR Health, “Summary of FAIR Health Phase I Rate Table Methodology, Addendum, March 2011,” *available at* <http://www.fairhealthus.org/sites/fairhealthus.org/files/Summary%20of%20FAIR%20He>

alth%20Phase%20I%20Rate%20Table%20Methodology%20Addendum%20March%202
011_0.pdf (last visited Jul. 1, 2011).

Food and Drug Administration. Elemental Analysis Manual: Section 3.4 Special Calculations.

Version 1 (June 2008), *available at*

<http://www.fda.gov/Food/ScienceResearch/LaboratoryMethods/ElementalAnalysisManualEAM/ucm205119.htm> (last visited June 29, 2011).

Food and Agriculture Organization of the United Nations. Guidelines for quality management in soil and plant laboratories (FAO Soils Bulletin – 74), *available at*

<http://www.fao.org/docrep/W7295E/w7295e08.htm> (last visited June 29, 2011).

Indiana Department of Environmental Management, Office of Air Quality. Chapter 13. Quality Assessment and Statistical Analysis of Air Monitoring Data, *available at*
http://www.in.gov/idem/files/oaq_qa_manual_chap_13.pdf (last visited June 29, 2011).

B. Books

Cohen, J. 1988. *Statistical power analysis for the behavioral sciences*. 2nd ed., New York: Taylor & Francis Group: New York.

Rubin, A. 2010. *Statistics for evidence-based practice and evaluation*. 2nd ed., Belmont, CA: Brooks/Cole.

Cramer, D. 1997. *Basic statistics for social research: step-by-step calculations and computer techniques using Minitab*. New York: Routledge.

Taylor, J.R. 1982. *An Introduction to Error Analysis: The Study of Uncertainties in Physical Measurements*, 2nd ed. United States: University Science Books.